

# AN INTEGRATED PS-IN SAR AND MACHINE LEARNING FRAMEWORK FOR BRIDGE DISPLACEMENT MONITORING

By

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# ABSTRACT

Ensuring the safety and long-term performance of bridge infrastructure requires reliable methods for monitoring structural behavior over time. Traditional structural health monitoring (SHM) systems often rely on in-situ sensors that provide detailed measurements, but are typically limited in spatial coverage and access to the bridge site. In contrast, satellite-based interferometric synthetic aperture radar (InSAR) enables millimeter-level displacement monitoring over large areas without the need of installing and maintaining sensors. This thesis develops a new approach for integrating the time-series modeling, SAR satellite interferometry and machine learning techniques, to better support data-driven structural monitoring. As employing ML techniques for structural investigations must be correctly applied, initially, a FEM model of a cantilever beam and dynamic loading was investigated and its response time-series modeling approaches, similar to the ones used in SHM, were examined, with particular attention to deep learning methods such as Long Short-Term Memory (LSTM) networks, multivariate time-series transformers and LSTM-based autoencoders. These models are reviewed and analyzed for their ability to capture complex temporal patterns in structural response data and their potential for supporting data-driven damage detection. Once these techniques were confirmed as accurately performing for structural applications, a real bridge was selected for monitoring with remote sensing methods (satellites) and used the ML techniques for the assessment of the measured responses. Thus, Persistent Scatterer InSAR (PS-InSAR) method was applied to derive displacement time series for persistent scatterer points, over five years, located on the Victoria Bridge in Montreal. Statistical and temporal features were extracted from the displacement signals and an unsupervised anomaly detection framework based on the Isolation Forest algorithm was developed to identify unusual displacement patterns. Spatial filtering, to ensure the neighborhood consistency of the identified anomalous points on the deck, and bridge deck-axis segmentation, to create regular bins of measured data that are easier to interpret statistically but structurally as well, were developed and implemented to improve the robustness of anomaly identification. These techniques are



newly developed in the current study. The proposed framework was extended to a multi-satellite analysis of PS-InSAR observations from Sentinel-1, RADARSAT Constellation Mission (RCM), and RADARSAT-2 to identify the challenges and compatibilities between the measurements of the same monitored structure. Having access to data from three different satellites tasked to monitor the same structure, Victoria Bridge in this case, is very rare and very valuable. Using an enhanced anomaly detection workflow that integrates statistical filtering and spatial constraints, displacement trends and anomaly patterns were compared across different satellites datasets to assess the consistency and reliability of satellite-based bridge monitoring. The PS-InSAR investigation of the Victoria Bridge, enhanced with anomaly detection using spatial filtering techniques, demonstrated that the proposed approach can effectively highlight spatial zones with concentrated anomalies, while improving the interpretability of satellite-derived displacement measurements. Together, these contributions illustrate the potential of combining satellite remote sensing and machine learning techniques to support scalable and data-driven approaches for long-term bridge monitoring.

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# LIST OF ABBREVIATIONS

| Abbreviation | Definition                                            |
|--------------|-------------------------------------------------------|
| AE           | Autoencoder                                           |
| AI           | Artificial Intelligence                               |
| APS          | Atmospheric Phase Screen                              |
| ASF          | Alaska Satellite Facility                             |
| AUC          | Area Under the Curve                                  |
| C-GMS        | Canadian Ground Motion Service                        |
| DEM          | Digital Elevation Model                               |
| DInSAR       | Differential Interferometric Synthetic Aperture Radar |
| DL           | Deep Learning                                         |
| ESD          | Enhanced Spectral Diversity                           |
| FEM          | Finite Element Method                                 |
| GNSS         | Global Navigation Satellite System                    |
| InSAR        | Interferometric Synthetic Aperture Radar              |
| iForest      | Isolation Forest                                      |
| iTree        | Isolation Tree                                        |
| IW           | Interferometric Wide Swath                            |
| LOS          | Line of Sight                                         |
| LSTM         | Long Short-Term Memory                                |
| MAD          | Median Absolute Deviation                             |

|          |                                                               |
|----------|---------------------------------------------------------------|
| ML       | Machine Learning                                              |
| MSE      | Mean Squared Error                                            |
| MTT      | Multivariate Time-Series Transformer                          |
| NDT      | Non-Destructive Testing                                       |
| PS       | Persistent Scatterer                                          |
| PSI      | Persistent Scatterer Interferometry                           |
| PS-InSAR | Persistent Scatterer Interferometric Synthetic Aperture Radar |
| R2       | RADARSAT-2                                                    |
| RCM      | RADARSAT Constellation Mission                                |
| RMSE     | Root Mean Squared Error                                       |
| RNN      | Recurrent Neural Network                                      |
| ROC      | Receiver Operating Characteristic                             |
| S1       | Sentinel-1                                                    |
| SAR      | Synthetic Aperture Radar                                      |
| SHAP     | SHapley Additive exPlanations                                 |
| SHM      | Structural Health Monitoring                                  |
| SLC      | Single Look Complex                                           |
| SNAP     | Sentinel Application Platform                                 |
| StaMPS   | Stanford Method for Persistent Scatterers                     |
| TOPSAR   | Terrain Observation with Progressive Scans SAR                |
| VV       | Vertical-Vertical Polarization                                |

# LIST OF SYMBOLS

| Symbol        | Definition                                                           |
|---------------|----------------------------------------------------------------------|
| $B_{\perp}$   | Perpendicular baseline between SAR acquisitions                      |
| $C_t$         | LSTM cell state at time step $t$                                     |
| $\tilde{C}_t$ | Candidate LSTM cell state at time step $t$                           |
| $c(n)$        | Average path length of unsuccessful searches in a binary search tree |
| $d$           | Dimension of an input data point                                     |
| $E[h(x)]$     | Expected path length of observation $x$ across isolation trees       |
| $f_t$         | LSTM forget-gate activation at time step $t$                         |
| $FFN(\cdot)$  | Feed-forward neural network operation                                |
| $H(i)$        | Harmonic number                                                      |
| $h_t$         | LSTM hidden state at time step $t$                                   |
| $h(x)$        | Path length of observation $x$ in an isolation tree                  |
| $i_t$         | LSTM input-gate activation at time step $t$                          |
| $k$           | Integer phase ambiguity associated with phase wrapping               |
| $N$           | Number of observations or time steps                                 |
| $o_t$         | LSTM output-gate activation at time step $t$                         |
| $P$           | Ground target position                                               |
| $P'$          | Ground target position after displacement                            |
| $PE$          | Positional encoding                                                  |
| $s(x, n)$     | Isolation Forest anomaly score for observation $x$                   |

|                                   |                                                         |
|-----------------------------------|---------------------------------------------------------|
| $t$                               | Time-step index                                         |
| $W$                               | Neural-network weight matrix                            |
| $W_f$                             | LSTM forget-gate weight matrix                          |
| $W_i$                             | LSTM input-gate weight matrix                           |
| $W_C$                             | LSTM candidate-cell weight matrix                       |
| $W_o$                             | LSTM output-gate weight matrix                          |
| $x_t$                             | Input vector at time step $t$                           |
| $X$                               | Input time-series sequence                              |
| $y_i$                             | Output of the self-attention layer at position $i$      |
| $Y$                               | Output or reconstructed sequence                        |
| $\alpha_{ij}$                     | Attention weight between sequence positions $i$ and $j$ |
| $\Delta\phi_{\text{int}}$         | Interferometric phase difference                        |
| $\Delta\phi_{\text{DInSAR}}$      | Differential interferometric phase                      |
| $\phi_{\text{Displ}}$             | Interferometric phase component caused by displacement  |
| $\phi_{\text{Topo}}$              | Topographic phase component                             |
| $\phi_{\text{Topo}}^{\text{res}}$ | Residual topographic phase caused by DEM errors         |
| $\phi^{\text{Atm}}$               | Atmospheric phase component                             |
| $\phi^{\text{Orb}}$               | Orbital phase error component                           |
| $\phi^{\text{Noise}}$             | Noise contribution to the interferometric phase         |
| $\lambda$                         | Radar wavelength                                        |
| $\sigma(\cdot)$                   | Sigmoid activation function                             |



# CHAPTER 1

## INTRODUCTION

### 1.1 BACKGROUND

Bridges are essential components of transportation networks that support the movement of people and goods and play a critical role in economic and social activities. However, many bridge structures worldwide are aging, and their individual structural performance is gradually affected by exposure to harsh environmental conditions, increased traffic loading, temperature variations and material degradation [1, 2]. Over time, these factors will lead to damage accumulation, stiffness reduction, or excessive deformation of the bridge structural elements. If such changes remain undetected, they can compromise structural safety and increase repair and maintenance costs.

Structural Health Monitoring (SHM) has been developed to assess structural condition and detect early signs of deterioration [1, 3]. Conventional bridge inspection methods rely largely on periodic visual inspections and localized non-destructive testing. While these approaches remain important, they have inherent limitations. Visual inspections are labor-intensive, subjective, and typically performed at extended time intervals, which may prevent the detection of subtle or progressive structural changes [3, 4]. Moreover, many bridges are not permanently instrumented, limiting the availability of continuous structural response data to help detect early signs of structural integrity issues.

In recent years, learning-based approaches have emerged as promising tools for improving structural monitoring. Advances in deep learning algorithms have enabled the analysis of complex time-series signals, such as displacement and acceleration responses, to detect structural damage patterns that may not be visible through traditional methods [5, 6]. Deep learning architectures such as Long Short-Term Memory (LSTM) networks and Transformer-based models have demonstrated strong capability in capturing temporal dependencies in sequential data [6, 7].

## 1.2. RESEARCH MOTIVATION

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These recent developments have opened new possibilities for automated damage identification in structural systems. At the same time, satellite-based remote sensing techniques, particularly Persistent Scatterer Interferometric Synthetic Aperture Radar (PS-InSAR), have enabled large-scale monitoring of millimeter-level displacements over long periods of time [8, 9]. Unlike local sensors used for SHM, PS-InSAR does not require on-site instrumentation and can provide spatially distributed displacement measurements across entire bridge decks. This makes it particularly attractive for monitoring structures that are difficult to instrument or access.

Despite these developments, existing approaches are often applied independently. Deep learning-based damage detection typically focuses on local dynamic response data, while PS-InSAR is commonly used for long-term displacement monitoring without integrating advanced machine learning analysis. Furthermore, systematic cross-validation of displacement behavior across different satellite missions remains limited in bridge applications [9]. As a result, there is a need for a unified framework that combines large-scale displacement monitoring, local damage detection and explainable anomaly analysis.

This thesis develops and validates advanced methodologies for structural monitoring. The work addresses both local dynamic damage detection using deep learning techniques and large-scale satellite-based displacement analysis using PS-InSAR data. While these approaches operate at different sensing scales and rely on distinct data sources, they collectively contribute to improving the reliability and analytical depth of modern structural health monitoring. Through controlled structural simulations and real-world satellite observations, this research advances methodological tools applicable to infrastructure monitoring, with particular emphasis on remote sensing for bridge systems.

## 1.2 RESEARCH MOTIVATION

Visual inspections are subjective and labor-intensive, while sensor-based monitoring systems often involve high installation and maintenance costs. Their spatial coverage is also fixed at the

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instrumented locations, leaving uninstrumented regions unobserved. For aging bridges where deterioration can initiate at unpredictable locations, this is a fundamental limitation.

Satellite-based remote sensing offers a fundamentally different approach. Persistent Scatterer Interferometric Synthetic Aperture Radar provides millimeter-scale displacement measurements from orbit, covering an entire bridge without any on-site instrumentation, without disrupting traffic or operations, and at a recurring cost far below that of permanently installed sensor networks. In principle, PS-InSAR can observe entire bridge networks simultaneously and capture long-term displacement records that no contact-based system could measure at comparable spatial coverage. Despite these advantages, its widespread adoption for bridge structural monitoring has been limited by a set of unresolved methodological challenges.

The first challenge is the proper spatial validation of PS-InSAR measurements on the structure. PS-InSAR records displacement histories at persistent scatterer points, but the physical correspondence between each PS point and a specific structural element is rarely established rigorously. Without this spatial grounding, it is unclear whether a given displacement reading reflects genuine structural behavior or noise of radar geometry, atmospheric noise, or localized thermal effects. Existing bridge-oriented studies have largely focused on displacement velocity and seasonal trend extraction, without providing a validated framework for attributing PS measurements to structural components and interpreting them in structural terms.

The second challenge is the detection and interpretation of anomalous displacement behavior. Long-term PS records are dominated by thermal expansion and gradual settlement, and identifying deviations that may signal developing structural problems or data quality issues requires systematic anomaly detection. Machine learning-based anomaly detection has seen limited application in PS-InSAR bridge monitoring, and the additional step of making anomaly detection interpretable, by explaining which displacement features drive each anomaly classification, has been largely neglected. Without interpretability, anomaly detection outputs are difficult for structural engineers to act upon.

A third challenge concerns cross-satellite consistency. Sentinel-1, RADARSAT-2, and the RADARSAT Constellation Mission differ in spatial resolution, radar frequency, incidence angle,

## 1.2. RESEARCH MOTIVATION

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and revisit schedule, all of which influence the density and distribution of persistent scatterers on a bridge deck. Whether anomaly patterns identified by one satellite are reproduced by another, within a unified analytical framework, remains largely unvalidated. In the sensor-based SHM domain, a parallel gap exists: systematic comparative evaluation of advanced time-series deep learning architectures, including Transformer-based models, under controlled structural damage conditions is still limited, with most studies evaluating a single model on a single dataset.

The aim of this thesis is to develop and validate a complete, integrated PS-InSAR and machine learning framework for bridge remote structural monitoring that directly addresses these gaps. Specifically, the framework implements a full PS-InSAR processing workflow for a real bridge, applies spatial filtering to improve the structural relevance of the sampled PS point set, integrates Isolation Forest anomaly detection to identify PS points with statistically abnormal displacement behavior, and incorporates SHAP-based explainability to trace each anomaly classification to specific, physically interpretable displacement features. The framework is extended to a multi-satellite context, covering Sentinel-1, RADARSAT-2, and RCM, to assess the consistency and robustness of results across satellite systems. In parallel, the thesis addresses the sensor-based SHM gap through the first systematic benchmarking of LSTM, Transformer, and autoencoder architectures for structural damage detection under consistent experimental conditions.

It is important to note that the primary contribution of this thesis is not the development of new machine learning algorithms, but rather the development of an integrated framework that adapts and combines existing methods for bridge structural health monitoring using satellite remote sensing. The deep learning models investigated in Chapter 3 are employed to advance the damage detection tools based on recorded structural response time-series at different points, which opens the path for practical applications in structural health monitoring. Chapters 4 and 5 present the methodology developed for integrating PS-InSAR measurements with machine learning techniques to improve the interpretation of bridge displacement response. Within this framework, monitoring bridge deck displacements provides continuous measurements of structural response and anomaly detection enables the identification of unusual displacement patterns that may warrant further investigation. By linking these complementary components

### 1.3. *RESEARCH OBJECTIVES*

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into a unified methodology, this research develops a novel, reliable and interpretable framework for satellite-based bridge monitoring, rather than proposing a new machine learning algorithm.

## 1.3 RESEARCH OBJECTIVES

The primary objective of this thesis is to advance satellite-based remote sensing of bridge structures by developing, implementing and validating an integrated PS-InSAR and machine learning framework for bridge displacement monitoring. To achieve this main goal, a series of specific objectives were defined and systematically pursued throughout the course of this study, including:

1. To evaluate advanced deep learning architectures for the detection and localization of damage in basic structural elements of a bridge, by employing trained and validated deep learning algorithms on simulated structural response data. This objective aims at identifying the techniques most suitable for structural integrity assessment of bridge components and most readily adaptable to real monitoring conditions.
2. To implement and refine a PS-InSAR-based displacement monitoring framework for the Victoria Bridge, enabling the processing and conversion of satellite radar imagery into actual displacements along the bridge deck, and supporting the reliable extraction and interpretation of long-term displacement time series. Through this research objective, the validation of the PS-InSAR is sought for a real bridge.
3. To integrate explainable machine learning-based anomaly detection into the PS-InSAR displacement analysis framework, in order to improve the interpretation of displacement data measured by satellite at different locations along the bridge deck, and to flag anomalous individual PS points and spatial clusters, distinguishing structurally meaningful deviations from faulty or noise-driven data.
4. To perform a cross-satellite comparative analysis of bridge displacement trends and anomaly patterns across Sentinel-1, RADARSAT-2, and the RADARSAT Constellation Mission, using consistent analytical procedures. A key motivation is to assess the trade-off between the

#### 1.4. *RESEARCH NOVELTY AND CONTRIBUTION*

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freely available but lower-density Sentinel-1 data and the higher-resolution but commercially restricted RADARSAT missions, and to determine the compatibility of multi-satellite displacement measurements for the Victoria Bridge, thereby broadening the applicability of satellite-based structural monitoring.

Together, these objectives support the development of more efficient and accessible satellite-based infrastructure assessment methods, contributing to the future design of early warning systems for the identification of structural anomalies in bridge structures and the partial replacement of costly on-site inspections.

### 1.4 RESEARCH NOVELTY AND CONTRIBUTION

This thesis advances structural remote sensing for bridge SHM through methodological developments in both potential anomaly detection and satellite-based displacement analysis. The work combines controlled structural simulations with real-world satellite observations, contributing to both deep learning-based SHM research and PS-InSAR-based bridge monitoring. The primary novelties of this research are summarized as follows:

1. Systematic evaluation of advanced time-series deep learning architectures for structural damage detection.

While deep learning has been applied in SHM, the structured comparison of recurrent (LSTM), autoencoder-based and Transformer-based models adapted for structural damage detection remain limited. This study introduces and evaluates a Multivariate Time-Series Transformer (MTT) architecture within a controlled structural damage simulation environment and compares it directly with LSTM-based approaches under consistent experimental conditions. Damage detection is interpreted based on acceleration response time series monitored at different points along a structural element. MTT application for dynamic structural response was never attempted by other researchers; thus, this represents a novel feature of the current research.

#### 1.4. RESEARCH NOVELTY AND CONTRIBUTION

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2. Developing and integrating spatial filtering and explainable anomaly detection into PS-InSAR-based bridge displacement analysis.

Although PS-InSAR has been widely used for structural displacement monitoring, its combination with machine learning-based anomaly detection and SHAP-based explainability for bridge applications was not yet attempted. This research extends PS-InSAR analysis beyond displacement trend visualization by introducing an Isolation Forest anomaly detection model trained on a nine-feature representation of each PS displacement time series, capturing long-term velocity, short-term variability, thermal sensitivity, trend and seasonal strength, autocorrelation, and distributional shape, and applying SHAP analysis to attribute each anomaly classification to its driving displacement features at the individual PS point level. A spatial filter was then developed to retain only anomalous PS points appearing in consistent spatial clusters along the bridge axis, thereby isolating displacements that reflect coherent structural behavior rather than isolated noise. The new spatial filtering procedure was embedded in the anomaly detection framework so that it can be directly applied to other bridge structures.

3. Cross-satellite validation of bridge displacement and anomaly patterns using a consistent analytical framework.

A novel approach pursued in the current study is the comparative assessment of displacement trends derived from different SAR satellite missions using identical processing and anomaly detection procedures. This thesis provides a structured cross-satellite analysis for the same structure, Victoria Bridge, monitored at overlapping and complementary time periods by the satellites Sentinel-1, RADARSAT-2 and the RADARSAT Constellation Mission, thus enabling consistency in displacements evaluation of satellite-based bridge monitoring results.

Beyond the methodological novelties introduced in this research, the thesis also provides several significant technical contributions related to bridge structural monitoring, InSAR-based displacement assessment and interpretable anomaly detection, as follows:

### 1.5. *RESEARCH OUTLINE*

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1. Development of a controlled finite element simulation framework for generating acceleration response datasets under multiple structural damage scenarios, enabling rigorous evaluation of deep learning models for structural damage detection.
2. Implementation and refinement of a PS-InSAR processing workflow for bridge displacement monitoring, addressing practical issues, such as interferogram selection, coherence variability and displacement trend stabilization in real-world datasets.
3. Application and validation of Isolation Forest-based anomaly detection combined with SHAP interpretation for identifying and explaining abnormal displacement behavior in long-term bridge monitoring data.
4. Comprehensive comparative analysis of displacement trends and anomaly distributions across multiple SAR satellite missions, providing insight into the stability and reliability of satellite-derived structural monitoring.

These novel contributions extend the practical applicability of the proposed PS-InSAR framework and support the development of more reliable approaches for identifying structural irregularities and collectively, these enhance methodological rigor in structural health monitoring while expanding the analytical capabilities available for damage detection and displacement assessment.

## 1.5 RESEARCH OUTLINE

As shown in Figure 1.1, the thesis is organized according to a publication-based format, where the main chapters correspond to peer-reviewed journal articles and their methodological extensions.

Chapter one introduces the research background, identifies the primary research gaps, and presents the novelty and contributions of the thesis. Chapter two provides a comprehensive review of structural health monitoring methodologies, including deep learning-based damage detection approaches and PS-InSAR-based displacement monitoring techniques. This chapter establishes



## 1.5. RESEARCH OUTLINE

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the theoretical and methodological foundations for the research contributions presented in subsequent chapters. Chapter three (Technical Paper 1) is based on the published journal article addressing deep learning-based structural damage detection. It presents the development of a finite element simulation framework for generating acceleration response data and provides a comparative evaluation of LSTM, LSTM-based Autoencoder, and Multivariate Time-Series Transformer architectures for structural damage identification. The selection of the three deep learning architectures investigated in Chapter 3 was motivated by their complementary capabilities for modeling structural time-series data rather than by arbitrary choice. LSTM was selected as a well-established recurrent architecture capable of learning long-term temporal dependencies, while the LSTM-based Autoencoder represents a reconstruction-based approach for identifying abnormal structural responses. The Multivariate Time-Series Transformer (MTT) was included because Transformer-based models had recently emerged as a powerful attention-based alternative for sequence modeling. By comparing these representative deep learning algorithms under identical structural damage scenarios, Chapter 3 provides a systematic evaluation of modern machine learning approaches for structural response analysis under controlled conditions, where both the structural response and the damage state are known. Such controlled environments are rarely available in real bridge monitoring, where only displacement measurements are available and the true structural condition is generally unknown. This progression establishes the methodological basis for the subsequent chapters by transitioning from the evaluation of machine learning methods under controlled conditions to the interpretation of real-world satellite-derived displacement measurements. Although acceleration and displacement characterize different aspects of structural response, both provide valuable information for understanding structural behavior. In this thesis, machine learning therefore serves different but complementary roles: supervised learning is employed to investigate damage detection from simulated structural responses, while unsupervised learning is used to interpret long-term bridge displacement behavior measured by PS-InSAR. Chapter four (Technical Paper 2) presents the PS-InSAR-based bridge displacement monitoring study. It describes the data processing methodology, refinement procedures, and the integration of Isolation Forest anomaly detection with SHAP-based interpretability for analyzing long-term displacement behavior of the Victoria Bridge in Montreal, QC. Chapter

### 1.5. *RESEARCH OUTLINE*

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five (Technical Paper 3) extends the PS-InSAR analysis through cross-satellite validation. It compares displacement trends and anomaly patterns derived from Sentinel-1, RADARSAT-2, and the RADARSAT Constellation Mission using consistent analytical procedures acquired over the Victoria Bridge. Chapter six provides an integrated discussion of the results obtained from the deep learning-based damage detection study and the satellite-based displacement monitoring investigations. This chapter synthesizes the methodological findings, discusses their implications for structural health monitoring practice, and evaluates the strengths and limitations of the proposed approaches. Chapter seven concludes the thesis by summarizing the main findings and contributions. It also outlines the limitations of the research and identifies potential directions for future work in data-driven structural monitoring.

## 1.5. RESEARCH OUTLINE

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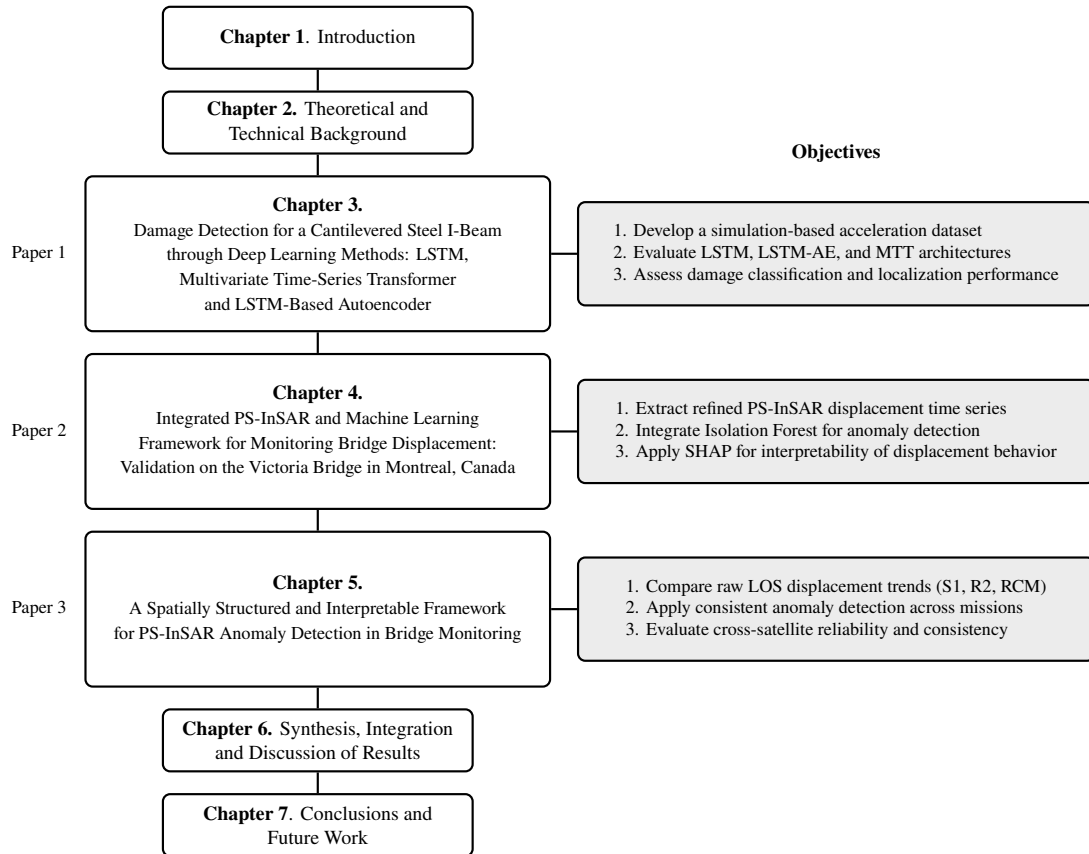


Figure 1.1: Thesis Organization

# CHAPTER 2

## LITERATURE REVIEW

### 2.1 STRUCTURAL HEALTH MONITORING FUNDAMENTALS

Structural Health Monitoring (SHM) is a systematic process aimed at assessing the condition of structures through the acquisition and analysis of structural response data. Over the past three decades, SHM has evolved from periodic inspection practices to continuous monitoring frameworks that integrate sensing technologies, signal processing, and data-driven analysis [3, 10]. The fundamental goal of SHM is to provide reliable information about structural integrity to support maintenance planning, safety evaluation, and long-term infrastructure management.

In civil infrastructure applications, SHM systems are designed to monitor bridges, buildings, and other critical structures subjected to environmental and operational loading. The primary objectives extend beyond simply identifying the presence of damage; they include determining its location, estimating its severity, and, in advanced applications, predicting its potential progression [11].

A widely accepted framework classifies damage identification into four hierarchical levels [12]:

1. Damage Detection – Determining whether damage exists.
2. Damage Localization – Identifying where the damage is located.
3. Damage Quantification – Estimating the extent or severity of the damage.
4. Prognosis – Predicting the remaining service life of the structure.

Most practical SHM implementations focus on detection and localization, as quantification and prognosis require more sophisticated modeling and long-term data availability.

## 2.1. *STRUCTURAL HEALTH MONITORING FUNDAMENTALS*

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Traditional structural condition assessment methods rely heavily on visual inspection and non-destructive testing (NDT) techniques. While these approaches provide valuable localized information, they are generally periodic, labor-intensive, and dependent on expert interpretation [13]. In addition, inspections may require access limitations or temporary traffic interruption, reducing their scalability for large infrastructure networks.

To overcome these limitations, sensor-based SHM systems have been developed to measure structural response parameters such as acceleration, strain, displacement, and modal characteristics. These systems enable continuous or near-real-time monitoring and provide insight into structural behavior under operational conditions [14]. However, challenges remain in optimal sensor placement, long-term maintenance, data management and cost-effectiveness, particularly for large-scale bridge networks.

Environmental and operational variability further complicate structural monitoring. Temperature fluctuations, humidity changes, traffic loads and other external factors can significantly influence measured structural responses. These variations may obscure or mimic damage-related changes, making it difficult to distinguish between environmental effects and genuine structural deterioration [15]. Robust monitoring strategies must therefore incorporate methods capable of accounting for such variability.

In recent years, remote sensing techniques have emerged as complementary tools to ground-based SHM systems. Satellite-based approaches, particularly interferometric synthetic aperture radar (InSAR), enable displacement monitoring over large spatial scales without direct contact with the structure [9]. These techniques are especially advantageous for long-span bridges and remote infrastructure. Nevertheless, translating displacement measurements into structural insight requires careful interpretation and understanding of measurement geometry and signal stability.

A persistent challenge in SHM is the limited availability of labeled damage data. Significant structural damage events are relatively rare, and controlled experimental datasets are often limited in diversity and scale. This scarcity motivates the use of simulation-based data generation and data-driven approaches capable of learning from complex structural response signals.

## 2.2. DEEP LEARNING FOR TIME-SERIES MODELING IN STRUCTURAL HEALTH MONITORING

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Overall, SHM represents a multidisciplinary field that integrates structural mechanics, sensing technologies, and advanced data analysis techniques. A clear understanding of these fundamentals is essential before introducing specific time-series modeling approaches and remote sensing methodologies, which are discussed in the following sections.

## 2.2 DEEP LEARNING FOR TIME-SERIES MODELING IN STRUCTURAL HEALTH MONITORING

Structural health monitoring systems generate large volumes of time-dependent data that describe the dynamic behavior of structures under operational and environmental loading. Typical measurements include acceleration, strain, displacement and vibration signals collected over extended periods. These signals contain information about stiffness changes, boundary condition variations, and potential damage evolution, but the relationship between raw measurements and structural condition is often indirect and complex [10, 11].

In vibration-based SHM, structural response signals are commonly analyzed in either the time domain, frequency domain, or time–frequency domain. Classical approaches rely on modal parameters such as natural frequencies, damping ratios and mode shapes, which are sensitive to changes in structural properties [15]. Variations in these parameters may indicate stiffness degradation or damage. However, extracting modal features typically requires signal preprocessing, system identification procedures, and assumptions about linearity and stationarity. Real-world structural signals are often influenced by operational and environmental variability. Temperature changes, traffic loading, and boundary condition fluctuations can alter dynamic characteristics without actual structural damage [16]. As a result, interpreting structural response signals requires careful distinction between normal variability and damage-induced changes.

Structural response measurements are inherently sequential. Each observation is temporally related to previous states of the system. Damage progression, environmental cycles, and operational loading introduce patterns that unfold over time rather than appearing instantaneously.

## 2.2. DEEP LEARNING FOR TIME-SERIES MODELING IN STRUCTURAL HEALTH MONITORING

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Traditional statistical approaches often treat measurements as independent observations, which can limit their ability to capture long-term dependencies. In contrast, time-series modeling techniques explicitly account for temporal correlations within the data [17]. This is particularly important for long-term monitoring, where gradual stiffness changes or slow displacement trends may be subtle but structurally meaningful.

Time-series modeling enables the identification of evolving patterns, abnormal deviations, and shifts in structural behavior. Capturing these temporal dependencies is therefore central to modern SHM frameworks, especially when continuous monitoring systems are deployed.

Historically, SHM relied heavily on manually engineered features derived from structural response data. Examples include peak amplitudes, modal frequencies, energy indices, and statistical descriptors such as kurtosis or root mean square (RMS) values [3]. These features are often selected based on domain expertise and physical interpretation.

While manual feature extraction can be effective, it presents limitations. The selected features may not fully capture complex nonlinear behavior, and their performance may degrade under environmental variability. Moreover, designing features for large-scale or heterogeneous structures can be time-consuming and problem specific.

The emergence of machine learning has introduced data-driven feature learning approaches, where models automatically extract relevant representations directly from raw or minimally processed signals [18]. Instead of relying solely on predefined statistical indicators, learning-based methods identify patterns embedded in high-dimensional data, potentially improving robustness and generalization.

Deep learning models, in particular, have demonstrated the ability to learn hierarchical representations of time-series data without explicit manual feature design [19]. This shift from handcrafted features to learned representations represents a fundamental transformation in SHM methodology and motivates the adoption of advanced temporal modeling architectures, which are introduced in the following subsections. LSTM networks, Transformer-based models, and autoencoder architectures were selected in this study because they represent three of the most

## 2.2. DEEP LEARNING FOR TIME-SERIES MODELING IN STRUCTURAL HEALTH MONITORING

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established and effective deep learning approaches for modeling sequential data, each offering complementary capabilities for learning temporal patterns in structural response signals.

### 2.2.1 LONG SHORT-TERM MEMORY (LSTM)

Long Short-Term Memory (LSTM) is a recurrent neural network (RNN) architecture developed to address the vanishing gradient problem observed in traditional RNNs. This issue arises when backpropagation generates very small gradient values, making it challenging to adjust the network weights effectively, thus leading to slow or ineffective learning. [6] introduced LSTM networks as a solution to this problem. LSTM incorporates memory cells, enabling the network to selectively retain or discard information at each time step. The network's architecture comprises memory cells linked to gates regulating information flow in and out of the cells. The core of LSTM is the cell state, which spans the entire chain with minor linear interactions. An LSTM unit (Fig. 2.1) includes input, output, and forget gates controlled by sigmoid activation functions, allowing them to take on values between zero and one. The forget gate determines how much information should be forgotten from the previous step (Eq.2.1), while the input gate determines how much new information should be stored in the memory cell by looking at the output from the previous step ( $h_{t-1}$ ) and input from current step ( $x_t$ ). as shown in Eqs. 2.2 and 2.3.

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad (2.1)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (2.2)$$

$$\tilde{C}_t = \tanh(W_C[h_{t-1}, x_t] + b_C) \quad (2.3)$$

The previous cell state  $C_{t-1}$  is updated by combining the retained information  $f_t C_{t-1}$  with the newly generated candidate values  $i_t \tilde{C}_t$ , as shown in Eq. 2.4. The near-linear path of the cell state across time steps allows gradients to propagate more effectively during backpropagation, thereby mitigating the vanishing gradient problem.



## 2.2. DEEP LEARNING FOR TIME-SERIES MODELING IN STRUCTURAL HEALTH MONITORING

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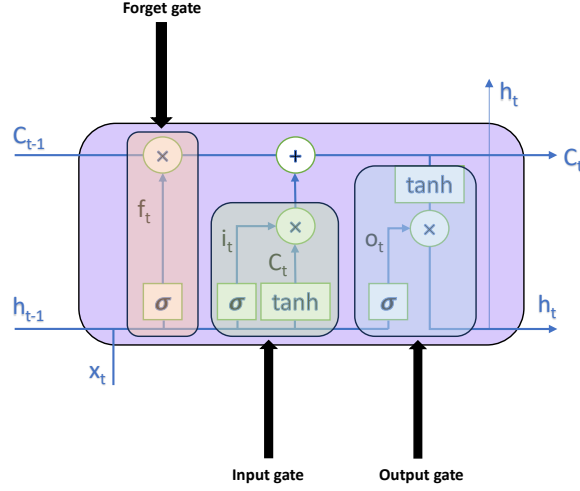


Figure 2.1: LSTM unit with gates.

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (2.4)$$

The output gate determines how much information should be output from the memory cell to the next time step (Eqs. 2.5 and 2.6):

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (2.5)$$

$$h_t = o_t * \tanh(C_t) \quad (2.6)$$

LSTM networks are widely used for modeling sequential data and are particularly suitable for capturing long-term dependencies in structural response time series.

### 2.2.2 MULTIVARIATE TIME-SERIES TRANSFORMER (MTT)

Traditional sequential models in deep learning, such as recurrent neural networks (RNNs) and long short-term memory networks (LSTMs), are designed to capture temporal patterns in sequential

## 2.2. DEEP LEARNING FOR TIME-SERIES MODELING IN STRUCTURAL HEALTH MONITORING

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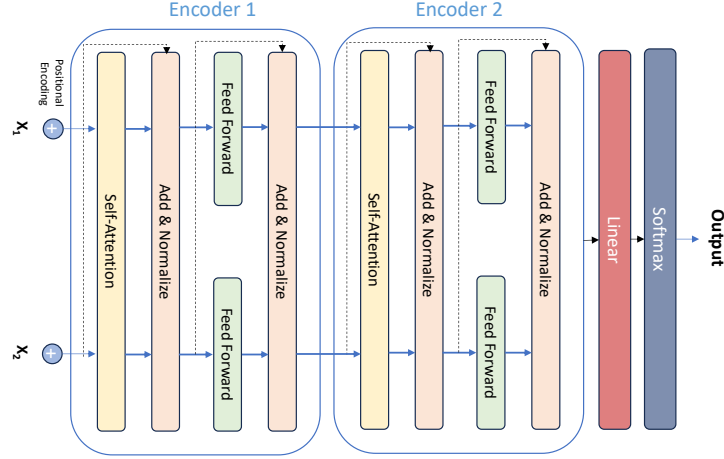


Figure 2.2: Transformer architecture with two encoder blocks.

data. However, these models present limitations, including limited parallelization capability and challenges in modeling very long-term dependencies. A significant advancement in sequence modeling was introduced through the Transformer architecture, a neural network model that addresses these limitations which significantly improved sequence modeling performance. The transformer, introduced by [20], represents a substantial change in sequence modeling design. Unlike traditional sequential models, transformers do not rely on recurrent connections. Instead, they are built upon self-attention mechanisms, enabling them to capture global dependencies in the input data. Furthermore, the transformer architecture has transcended its original domain and found applications in diverse fields, including computer vision, speech recognition, and time-series analysis [21]. Its versatility and effectiveness in capturing complex patterns make it a fundamental building block in modern deep-learning architectures. The transformer model can be represented as follows (Fig. 2.2) :

- Input representation

Let  $X = \{x_1, x_2, \dots, x_n\}$  be multivariate time-series data where  $x_i \in \mathbb{R}^d$  represents the  $i$ -th data point with  $d$  dimensions.

## 2.2. DEEP LEARNING FOR TIME-SERIES MODELING IN STRUCTURAL HEALTH MONITORING

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- Positional encoding

Unlike RNNs and LSTMs, transformers do not inherently understand the order of elements in a sequence due to their permutation invariance. To incorporate sequence order information, positional encodings are added to the input embeddings. These encodings provide the model with information about the positions of elements in the input sequence, allowing the transformer to distinguish between different positions. These encodings are denoted by,  $PE = \{pe_1, pe_2, \dots, pe_n\}$ , capture the sequential order of data points.

- Self-attention mechanism

At the heart of the transformer is the self-attention mechanism, which allows the model to weigh the importance of different elements in the input sequence when making predictions. The attention weights  $\alpha_{ij}$  are computed using scaled dot-product attention based on query, key, and value projections of the input embeddings [20]. This mechanism enables the transformer to capture relationships between elements that are arbitrarily far apart in the input sequence, addressing the challenge of long-range dependencies. The self-attention mechanism computes a set of attention weights  $\alpha_{ij}$  based on the input data and positional encodings. The output  $Y = \{y_1, y_2, \dots, y_n\}$  of the self-attention layer is calculated as a weighted sum of the input data:

$$y_i = \sum_{j=1}^n \alpha_{ij}(x_j + pe_j) \quad (2.7)$$

- Multi-head attention

To enhance the model's representational capacity, transformers use multi-head attention, where the self-attention mechanism operates in parallel across multiple projection subspaces. Unlike recurrent models, the self-attention mechanism enables direct modeling of dependencies between any two time steps, regardless of their temporal distance. This parallel processing allows the model to focus on different aspects of the input data simul-

## 2.2. DEEP LEARNING FOR TIME-SERIES MODELING IN STRUCTURAL HEALTH MONITORING

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taneously, leading to more expressive and accurate representations.

- Feed-forward neural network

After the self-attention layers, the transformer employs feed-forward neural networks at each position, further enhancing the model's ability to capture complex patterns in the data. The feed-forward neural network is applied element-wise to each position:

$$FFN(y_i) = W_2 \text{ReLU}(W_1 y_i + b_1) + b_2 \quad (2.8)$$

where  $W_1$ ,  $b_1$ ,  $W_2$  and  $b_2$  are learnable parameters. The combination of self-attention and feed-forward layers enables transformers to capture intricate patterns in multivariate time-series data, making them a powerful tool for various applications. In structural health monitoring applications, multivariate time-series transformers can be employed to analyze acceleration response data for damage identification tasks.

### 2.2.3 LSTM-BASED AUTOENCODER

Autoencoders are neural network architectures commonly used for representation learning through self-supervised reconstruction tasks. They consist of an encoder that maps input data to a lower-dimensional representation and a decoder that reconstructs the original data. By minimizing reconstruction error, autoencoders learn compact latent representations of the input data (Fig. 2.3).

LSTM autoencoders combine Long Short-Term Memory (LSTM) networks with the autoencoder framework to model sequential data. LSTMs capture temporal dependencies, while the autoencoder structure learns latent representations and reconstructs the sequence. During training, the model learns to reconstruct normal sequences by minimizing the reconstruction loss. Anomalies are identified by evaluating the reconstruction error of unseen sequences relative to the distribution observed during training. The loss function measures the discrepancy between

## 2.2. DEEP LEARNING FOR TIME-SERIES MODELING IN STRUCTURAL HEALTH MONITORING

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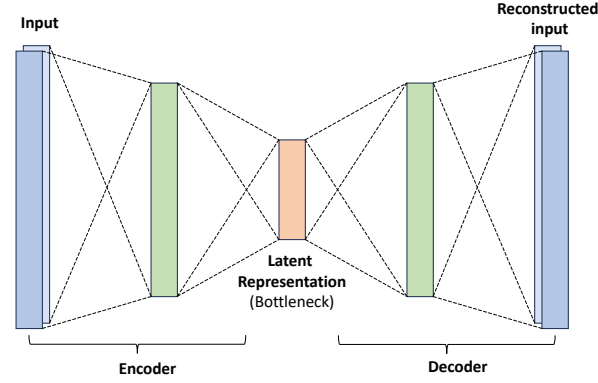


Figure 2.3: LSTM autoencoder for anomaly detection.

the input sequence  $X$  and the reconstructed sequence  $Y$ . Mean Squared Error (MSE) is commonly used as the loss function for autoencoders:

$$\mathcal{L} = \frac{1}{N} \sum_{i=1}^N (x_i - y_i)^2 \quad (2.9)$$

Where  $N$  is the number of time steps in the input sequence, and  $x_i$ ,  $y_i$  are input and output at time step  $i$ , respectively. This technique is particularly suitable for detecting subtle deviations in time-series data due to its reconstruction-based learning mechanism. Since anomalous data from real structures are often scarce, reconstruction-based approaches trained primarily on normal data are considered practical for structural condition evaluation in civil engineering applications.

In structural health monitoring contexts, LSTM-based autoencoders can be applied to acceleration response data to identify abnormal structural behavior associated with potential damage.

## 2.3 SYNTHETIC APERTURE RADAR INTERFEROMETRY AND PS-IN SAR

Interferometric Synthetic Aperture Radar (InSAR) is a remote sensing technique that allows for precise measurement of ground surface deformations by analyzing the phase difference between radar signals acquired at different times. Unlike optical remote sensing, which depends on sunlight, InSAR operates in the microwave spectrum, making it capable of capturing high-resolution images in all weather conditions and during both day and night [22]. This capability has made InSAR a valuable tool in a wide range of applications, including natural hazard monitoring, land subsidence detection, and infrastructure health assessment. A significant advancement in InSAR technology is Persistent Scatterer Interferometry (PS-InSAR), which enhances the technique's reliability by focusing on long-term stable scatterers, typically found in urban environments or on man-made structures. By analyzing these persistent scatterers over multiple SAR acquisitions, PS-InSAR enables long-term displacement monitoring with millimeter-scale accuracy, overcoming some of the limitations of conventional InSAR methods [23].

### 2.3.1 FUNDAMENTALS SAR AND IN SAR

Synthetic Aperture Radar (SAR) is an active remote sensing technology that transmits microwave signals toward the Earth's surface and records the backscattered signals to generate high-resolution images. Unlike optical sensors, which rely on reflected sunlight, SAR sensors actively illuminate their target, making them suitable for monitoring surface changes across different time periods [24]. The essential principle behind InSAR is determining the interferometric phase difference, which occurs when two SAR images of the same area are acquired at different times, or from slightly different angles. This phase difference can be used to extract information regarding the terrain elevation and surface displacement (Fig. 2.4).

An interferogram is generated by combining two SAR images, where the phase differences between corresponding pixels represent either topographic height variations or displacement

### 2.3. SYNTHETIC APERTURE RADAR INTERFEROMETRY AND PS-INSAR

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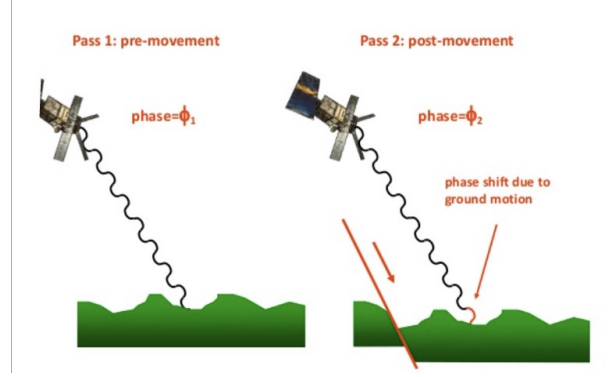


Figure 2.4: Illustration of SAR system acquiring two images at different times, showing the concept of interferometric phase differences [25].

along the sensor's line of sight (LOS). The interpretation of this phase information, however, requires careful processing due to inherent ambiguities in the data. The phase is wrapped between  $-\pi$  and  $+\pi$ , meaning that differences greater than one cycle appear as discontinuities. To derive meaningful displacement or topographic values, phase unwrapping techniques must be applied to convert these discontinuous wrapped phase values into continuous displacement estimates [26].

The interferometric phase measured in Differential Interferometric Synthetic Aperture Radar (DInSAR) and Persistent Scatterer Interferometry (PSI) is influenced by multiple factors including geometry, target motion, atmospheric delays, and system noise. The fundamental equations describing these contributions are summarized here based on the work of Crosetto et al. [27].

Assuming a ground target  $P$ , the radar phase measured from the satellite at acquisition time  $M$  is:

$$\phi_M = \phi_M^{\text{geom}} + \phi_M^{\text{scatt}} = \frac{4\pi}{\lambda} MP + \phi_M^{\text{scatt}} \quad (2.10)$$

where  $\lambda$  is the radar wavelength,  $MP$  is the slant-range distance between the sensor and the target, and  $\phi_M^{\text{scatt}}$  is the phase shift caused by the target's backscattering characteristics.

### 2.3. SYNTHETIC APERTURE RADAR INTERFEROMETRY AND PS-INSAR

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For a second acquisition from satellite position  $S$ , the phase is:

$$\phi_S = \phi_S^{\text{geom}} + \phi_S^{\text{scatt}} = \frac{4\pi}{\lambda} SP + \phi_S^{\text{scatt}} \quad (2.11)$$

The interferometric phase difference between the two acquisitions becomes:

$$\Delta\phi_{\text{int}} = \phi_S - \phi_M = \frac{4\pi}{\lambda}(SP - MP) + (\phi_S^{\text{scatt}} - \phi_M^{\text{scatt}}) \quad (2.12)$$

If the target moves to a new position  $P'$  between acquisitions, the second measurement becomes:

$$\phi_S = \frac{4\pi}{\lambda} SP' + \phi_S^{\text{scatt}} \quad (2.13)$$

So the new interferometric phase difference is:

$$\Delta\phi_{\text{int}} = \frac{4\pi}{\lambda}(SP' - MP) + (\phi_S^{\text{scatt}} - \phi_M^{\text{scatt}}) \quad (2.14)$$

This phase difference can be decomposed into two components: one related to topography, and the other to displacement:

$$\Delta\phi_{\text{int}} = \underbrace{\frac{4\pi}{\lambda}(SP - MP)}_{\phi_{\text{Topo}}} + \underbrace{\frac{4\pi}{\lambda}(SP' - SP)}_{\phi_{\text{Displ}}} + (\phi_S^{\text{scatt}} - \phi_M^{\text{scatt}}) \quad (2.15)$$

By removing the simulated topographic phase  $\phi_{\text{Topo}}^{\text{simu}}$  from the total phase, the differential interferometric phase becomes:

$$\Delta\phi_{\text{DInSAR}} = \Delta\phi_{\text{int}} - \phi_{\text{Topo}}^{\text{simu}} = \phi_{\text{Displ}} \quad (2.16)$$



### 2.3. SYNTHETIC APERTURE RADAR INTERFEROMETRY AND PS-INSAR

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The displacement term corresponds to motion projected along the radar line-of-sight direction. In practice, however, the observed phase includes additional components due to errors and noise:

$$\Delta\phi_{\text{DInSAR}} = \phi_{\text{Displ}} + \phi_{\text{Topo}}^{\text{res}} + \left(\phi_S^{\text{Atm}} - \phi_M^{\text{Atm}}\right) + \left(\phi_S^{\text{Orb}} - \phi_M^{\text{Orb}}\right) + \phi^{\text{Noise}} + 2\pi k \quad (2.17)$$

Here:

- $\phi_{\text{Topo}}^{\text{res}}$  is the residual topographic phase due to Digital Elevation Model (DEM) inaccuracies.
- $\phi^{\text{Atm}}$  and  $\phi^{\text{Orb}}$  represent atmospheric and orbital errors, respectively.
- $\phi^{\text{Noise}}$  includes decorrelation noise.
- $2\pi k$  accounts for the phase wrapping ambiguity.

These equations form the theoretical basis of PS-InSAR, where the goal is to isolate the displacement component  $\phi_{\text{Displ}}$  by minimizing the effects of all other error sources using long time series and stable reflectors.

#### 2.3.2 LIMITATIONS IN CONVENTIONAL InSAR AND THE ROLE OF PS-INSAR

While InSAR provides a powerful means of monitoring surface deformations, traditional methods face several limitations. One of the main challenges is temporal decorrelation, when changes in surface scattering characteristics between acquisitions reduce interferometric coherence and making it difficult to extract reliable phase measurements. Similarly, geometric decorrelation arises from spatial baseline differences between acquisitions, which cause variations in viewing geometry, particularly in rough terrain, where steep slopes can introduce inconsistencies in phase alignment. Another major challenge is the presence of atmospheric delays, where variations in humidity, pressure, and temperature cause additional phase delays, leading to inaccuracies in displacement measurements. Large temporal and spatial baselines can significantly reduce coherence, limiting the applicability of conventional InSAR for long-term monitoring. [23].

### 2.3. SYNTHETIC APERTURE RADAR INTERFEROMETRY AND PS-INSAR

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Figure 2.5: PS points over an area, with color-coded displacement trends [28].

To overcome these limitations, PS-InSAR was developed as an extension of conventional InSAR techniques. Rather than relying on all interferometric pixels, PS-InSAR identifies and analyzes a subset of highly coherent points known as Persistent Scatterers (PS), stable radar reflectors exhibiting consistent phase behavior over time. These PS points, such as: fixed infrastructure points or exposed bedrock, exhibit high coherence over multiple SAR acquisitions, enabling long-term displacement monitoring with minimal interference from decorrelation effects (Fig. 2.5). PS-InSAR exploits long temporal series and spatial correlation models to estimate and mitigate atmospheric phase components, significantly improving the reliability of results [26].

#### 2.3.3 GEOMETRY, SIGNAL COMPONENTS, AND PROCESSING CONCEPTS IN INSAR AND PS-INSAR

Interpreting InSAR and PS-InSAR results requires a clear understanding of the geometric configuration of SAR acquisitions, the physical components of the interferometric signal, and the key processing steps involved in deformation retrieval. The measured interferometric phase is influenced not only by ground displacement but also by imaging geometry, atmospheric effects,

### 2.3. SYNTHETIC APERTURE RADAR INTERFEROMETRY AND PS-INSAR

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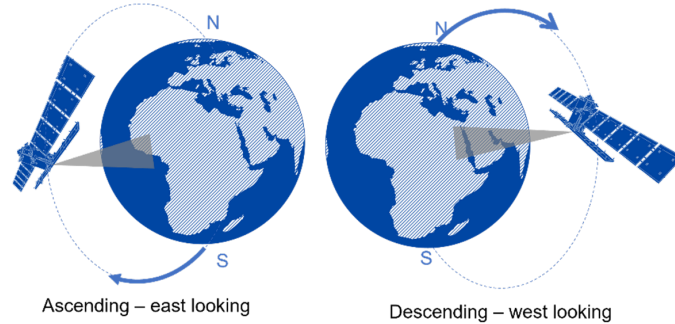


Figure 2.6: Ascending and Descending satellite pass [29].

orbital uncertainties, and signal decorrelation. This section therefore outlines the core geometric principles, signal components, and processing concepts that form the basis of reliable deformation analysis in both conventional InSAR and PS-InSAR applications.

One of the primary considerations in SAR imaging is the satellite's orbit geometry, which determines whether data is acquired in an ascending or descending pass. Most SAR satellites are right-looking systems, meaning that ascending passes typically observe targets from an eastward-looking geometry and descending passes from a westward-looking geometry. In an ascending pass, the satellite moves from south to north, capturing radar signals with an eastward-looking sensor, while in a descending pass, the satellite moves from north to south, capturing data with a westward-looking sensor (Fig. 2.6). This distinction is important because different orbit directions provide different perspectives of surface deformation, and combining data from both passes can help disentangle horizontal and vertical displacement components in deformation analysis [24].

Using InSAR analysis, two SAR images captured at different times, the master image and the secondary image, are used to measure displacements. The master image serves as a reference, while the secondary image is compared against it to detect phase differences caused by surface movement. The selection of an appropriate master image influences interferometric coherence and overall quality. Factors such as temporal baseline, perpendicular baseline, and overall coherence influence this selection. In PS-InSAR, multiple secondary images are used over time to track

### 2.3. SYNTHETIC APERTURE RADAR INTERFEROMETRY AND PS-INSAR

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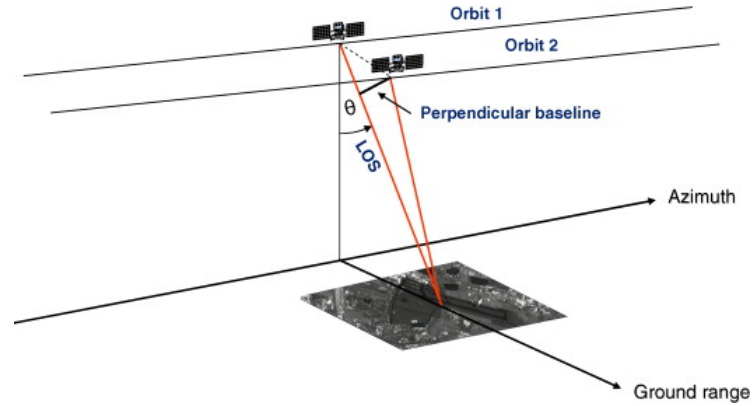


Figure 2.7: A SAR system from a satellite [32].

long-term structural displacements by analyzing stable scatterers, known as Persistent Scatterers (PS) [26].

An important factor in interferometric processing is the baseline, which refers to the spatial separation between two SAR acquisitions. The perpendicular baseline is the projection of this separation perpendicular to the sensor's line of sight (LOS) and determines the sensitivity of InSAR to topographic variations (Fig. 2.7). A very short perpendicular baseline reduces sensitivity to topography, whereas a very long baseline may decrease coherence. [30]. The temporal baseline, on the other hand, refers to the time interval between two SAR acquisitions. A shorter temporal baseline is more effective for detecting rapid deformation events such as earthquakes, while a longer temporal baseline is ideal for monitoring slow-moving processes like land subsidence or seasonal deformations [22].

SAR data is initially recorded in slant-range coordinates (Fig. 2.7), meaning that distances are measured directly from the satellite to the ground target. However, for geospatial analysis, these data must be transformed into ground-range coordinates, which represent actual geographic distances on the Earth's surface. The transformation process involves geocoding and orthorectification, which correct for distortions caused by terrain elevation and satellite viewing angle variations [31].

### 2.3. SYNTHETIC APERTURE RADAR INTERFEROMETRY AND PS-INSAR

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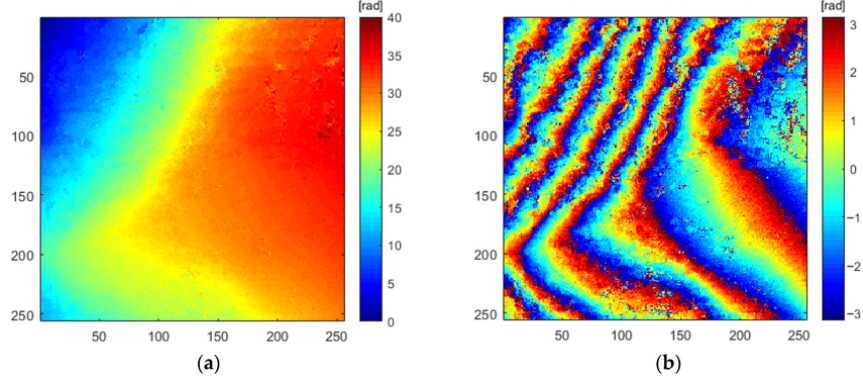


Figure 2.8: Illustration of unwrapped (a) and wrapped (b) phase measurements of a SAR image [33].

InSAR results rely heavily on the phase measurements, and understanding the difference between wrapped phase and unwrapped phase is fundamental to displacement analysis (Fig. 2.8). The wrapped phase, which is the raw interferogram measured between two SAR captures, is recorded in a cyclic range of  $-\pi$  to  $+\pi$  radians, meaning that any displacement greater than one wavelength appears discontinuous. Phase unwrapping is the process of converting these cyclic measurements into a continuous phase signal, ensuring that real-world displacement values can be extracted accurately [30].

The line-of-sight (LOS) displacement represents the motion component measured along the radar beam direction, rather than in purely horizontal or vertical terms. Since SAR sensors only capture deformation along their viewing direction, additional processing is required to decompose displacement into east-west, and vertical components when needed. For near-polar orbiting satellites such as Sentinel-1, the LOS direction is primarily sensitive to vertical and east-west displacement components, with limited sensitivity to north-south motion [26].

The choice of radar wavelength affects how SAR interacts with the Earth's surface. Different SAR systems operate in various frequency bands, each suited for specific applications (Fig. 2.9). The C-band (used in Sentinel-1, ENVISAT, RADARSAT-2, and RADARSAT Constellation Mission (RCM)) has a moderate wavelength and is well-suited for infrastructure monitoring. The L-band (used in ALOS-2, SAOCOM, and NiSAR, becoming operational in July 2025) has a

### 2.3. SYNTHETIC APERTURE RADAR INTERFEROMETRY AND PS-INSAR

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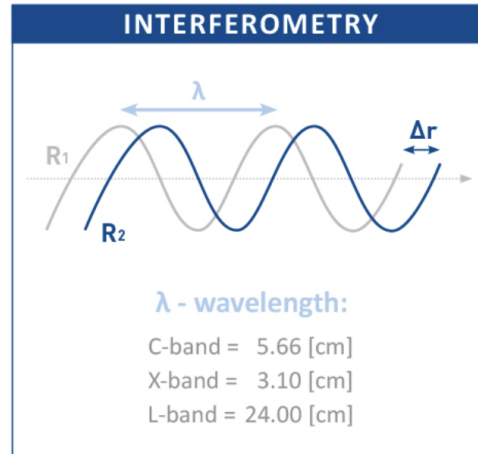


Figure 2.9: SAR bands and their wavelengths [29].

longer wavelength, allowing it to penetrate through vegetation and better capture slow-moving displacements of natural landscapes. The X-band (used in TerraSAR-X, COSMO-SkyMed) has a shorter wavelength and provides high-resolution imagery, making it ideal for urban monitoring but more sensitive to changes in surface conditions [23].

Another important characteristic of SAR imagery is its spatial resolution, which refers to the smallest detectable feature in an image. High-resolution SAR sensors provide more detailed observations but require increased data storage and processing power. The resolution also depends on factors such as azimuth resolution, which is determined by the length of the synthetic aperture, and range resolution, which depends on the radar pulse characteristics [24].

A critical pre-processing step in InSAR analysis is coregistration, which involves precisely aligning multiple SAR images to ensure that corresponding pixels in different acquisitions represent the same ground features. Accurate coregistration is essential for maintaining phase consistency and preventing misalignment artifacts in interferometric results [22].

The coherence of an interferogram is another key factor in data quality assessment. Coherence measures the similarity between two SAR images, with values ranging from 0 (no coherence) to 1 (perfect coherence). High coherence is required for accurate deformation measurements, but

### 2.3. SYNTHETIC APERTURE RADAR INTERFEROMETRY AND PS-INSAR

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it can be affected by temporal decorrelation (changes in surface properties over time), geometric decorrelation (differences in satellite viewing angles), and volumetric decorrelation (scattering from vegetation or rough terrain) [34].

In PS-InSAR, selecting Persistent Scatterers (PS) is a critical step. PS points are identified based on their high coherence and stable phase characteristics across multiple acquisitions. PS identification often relies on amplitude stability or phase stability metrics over long time series. Unlike traditional InSAR, which analyzes phase changes across all pixels, PS-InSAR isolates these long-term stable scatterers, allowing for more reliable deformation monitoring in urban and infrastructure settings [26].

To improve the accuracy of displacement measurements, tropospheric phase components are estimated and mitigated using spatial-temporal filtering approaches to remove atmospheric noise, which can cause artificial phase variations. Additionally, orbital corrections are performed to eliminate errors caused by minor satellite orbit inaccuracies [35].

#### 2.3.4 APPLICATIONS OF PS-INSAR IN STRUCTURAL AND BRIDGE MONITORING

Persistent Scatterer Interferometric Synthetic Aperture Radar (PS-InSAR) has evolved into a mature remote sensing technique for monitoring long-term ground and infrastructure deformation. Originally developed for geophysical applications such as land subsidence and slope instability, PS-InSAR has progressively been adapted for structural health monitoring (SHM) of large civil infrastructure, including bridges, buildings, and urban networks [8, 27].

One of the primary advantages of PS-InSAR in structural monitoring is its ability to measure millimeter-scale displacements over wide spatial extents without requiring physical access to the structure. This makes it particularly attractive for aging bridges and remote infrastructure where continuous in-situ instrumentation may be costly or impractical. Unlike conventional ground-based monitoring systems, PS-InSAR provides historical displacement information derived from archived satellite data, enabling retrospective assessment of structural behavior over several years [27].

### 2.3. SYNTHETIC APERTURE RADAR INTERFEROMETRY AND PS-INSAR

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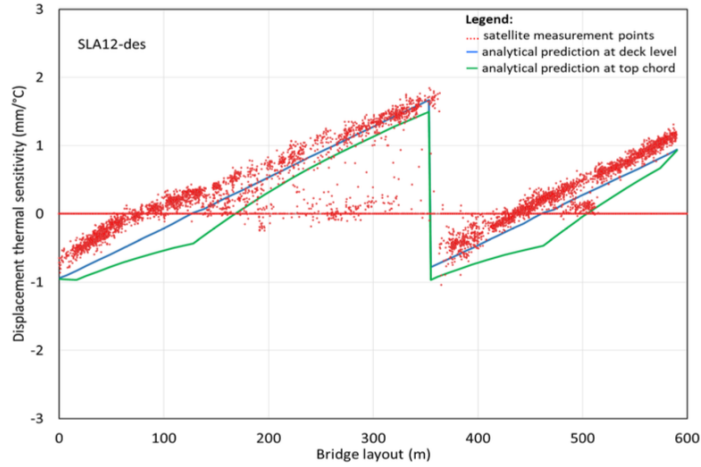


Figure 2.10: Comparison between InSAR and predicted thermal sensitivity data for the LOS direction obtained from the SLA12-des stack (Jacques Cartier Bridge; May 2016–September 2018) [37].

Bridge monitoring using PS-InSAR has received increasing attention in recent years. Studies have demonstrated that stable structural elements such as railings, expansion joints, metallic components, and other reflective surfaces can serve as persistent scatterers, allowing reliable time-series displacement retrieval [36, 37]. For example, Cusson et al. [36] investigated long-term displacement trends of the North Channel Bridge in Ontario and showed that thousands of stable PS points could be identified on bridge railings, significantly enhancing displacement measurement reliability. Their work also emphasized the importance of accounting for thermal expansion effects when interpreting displacement time series. In a subsequent study, Cusson et al. [37] introduced an early warning framework integrating PS-InSAR-derived displacements with thermal sensitivity analysis, demonstrating the feasibility of satellite-based bridge deformation monitoring at millimeter precision (Fig. 2.10).

Other research efforts have explored the integration of PS-InSAR with ground-based sensors such as GNSS systems to improve displacement interpretation and validation [38, 39]. Combining satellite-based observations with independent measurements enhances confidence in displacement trends and supports multi-source structural assessment. These studies highlight



### 2.3. *SYNTHETIC APERTURE RADAR INTERFEROMETRY AND PS-INSAR*

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the growing recognition of PS-InSAR as a complementary tool rather than a replacement for traditional SHM systems.

More recent studies have extended the application of PS-InSAR beyond displacement measurement toward the structural interpretation of bridge behavior and the development of automated analysis frameworks. Long-term satellite InSAR observations have demonstrated that temperature-induced displacement patterns can be associated with individual bridge spans and structural components, highlighting the importance of interpreting satellite-derived measurements within the structural context of the bridge [40]. Clustering-based approaches have also been proposed to automatically group persistent scatterer displacement time series according to their spatial and temporal characteristics, reducing the need for manual interpretation while improving the efficiency of bridge-scale PS-InSAR analysis [41]. More recently, multi-track InSAR observations have been integrated with environmental information and structural knowledge through Kalman filtering to reconstruct three-dimensional bridge displacements, with the reconstructed displacements showing good agreement with independent GNSS measurements [42]. Collectively, these studies demonstrate a growing shift from using PS-InSAR solely as a displacement measurement tool toward more comprehensive frameworks that support structural interpretation, automated analysis, and integration with complementary monitoring techniques for bridge structural health monitoring.

Despite these advances, the application of PS-InSAR to bridge monitoring presents several practical challenges. Bridges are relatively small and slender structures compared to typical geotechnical targets, and the density of persistent scatterers may vary significantly depending on material properties and viewing geometry. Atmospheric delays, orbital inaccuracies, and decorrelation effects can introduce phase noise that complicates displacement interpretation, particularly for short temporal baselines or rapidly changing environmental conditions [27, 34]. Furthermore, since PS-InSAR measures displacement only along the satellite's line-of-sight (LOS), additional processing or multi-orbit data are required to decompose motion into vertical and horizontal components.

## 2.4. ANOMALY DETECTION AND EXPLAINABLE MACHINE LEARNING IN STRUCTURAL MONITORING

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Another important consideration is the sensitivity of PS-InSAR measurements to thermal-induced structural expansion. Several studies have shown that seasonal temperature variations can dominate long-term displacement trends in steel bridges, making it necessary to distinguish between normal thermoelastic behavior and potential structural anomalies [36, 37]. This distinction is critical when PS-InSAR data are used for structural health assessment rather than purely geometric monitoring.

Overall, the literature indicates that PS-InSAR is a powerful and increasingly reliable tool for large-scale infrastructure monitoring. However, its effective application to bridge SHM requires careful processing, validation, and interpretation. While significant progress has been made in extracting displacement time series from satellite data, fewer studies have explored how these time series can be systematically analyzed using data-driven methods to detect abnormal structural behavior. This gap motivates the integration of PS-InSAR displacement monitoring with machine learning-based anomaly detection, which is explored in this thesis.

## 2.4 ANOMALY DETECTION AND EXPLAINABLE MACHINE LEARNING IN STRUCTURAL MONITORING

### 2.4.1 ANOMALY DETECTION IN STRUCTURAL HEALTH MONITORING

Structural health monitoring systems are often deployed to detect changes in structural behavior over time. In many real-world applications, however, clear labels distinguishing “healthy” and “damaged” states are unavailable. Structural damage events are relatively rare, and collecting sufficient labeled data for supervised learning is often impractical or economically infeasible. As a result, anomaly detection has emerged as an attractive alternative framework in SHM research [43, 44].

Anomaly detection, sometimes referred to as novelty detection, focuses on identifying observations that deviate significantly from the dominant behavior of a system. In structural monitoring,

## 2.4. ANOMALY DETECTION AND EXPLAINABLE MACHINE LEARNING IN STRUCTURAL MONITORING

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anomalies may correspond to unusual vibration patterns, unexpected displacement trends, or deviations from thermoelastic behavior. Rather than explicitly modeling every possible damage scenario, anomaly detection methods learn the characteristics of typical structural responses and flag observations that fall outside this learned distribution [45].

Traditional anomaly detection approaches in SHM have included statistical process control, threshold-based techniques, and model residual analysis [46]. While these methods are conceptually straightforward, they may struggle when environmental and operational variability strongly influence the measured response. Temperature fluctuations, traffic loading, and seasonal effects can produce significant variations in vibration or displacement signals, complicating the distinction between normal variability and structural deterioration.

Machine learning has introduced more flexible anomaly detection techniques capable of handling high-dimensional and nonlinear structural response data. Both supervised and unsupervised approaches have been explored. Supervised classification methods require labeled damaged data, which are rarely available in practice. In contrast, unsupervised methods rely only on data representing normal behavior and are therefore more aligned with real-world monitoring scenarios [44, 47].

In the context of displacement monitoring using PS-InSAR, anomaly detection plays a particularly important role. Satellite-derived displacement time series may reflect long-term structural trends, seasonal thermal expansion, and environmental noise. Detecting subtle deviations from expected structural behavior requires methods capable of distinguishing statistically unusual patterns from normal temperature-induced structural response. For this reason, unsupervised anomaly detection methods provide a suitable framework for analyzing PS-InSAR displacement features without relying on predefined damage labels.

### 2.4.2 ISOLATION FOREST

Isolation Forest (iForest) is an unsupervised anomaly detection algorithm designed to identify rare and structurally different observations within a dataset [48]. Unlike density-based or distance-

## 2.4. ANOMALY DETECTION AND EXPLAINABLE MACHINE LEARNING IN STRUCTURAL MONITORING

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based methods that attempt to model the distribution of normal data, Isolation Forest is built on the principle that anomalies are easier to isolate because they are both infrequent and different from the majority of observations [49]. Isolation Forest was selected in this research because it is an efficient unsupervised algorithm that can identify anomalies in high-dimensional feature spaces without requiring labeled training data or assumptions about the underlying data distribution. These characteristics make it particularly well suited for analyzing PS-InSAR displacement features, where anomalous structural behavior is rare, diverse, and difficult to label in advance.

The algorithm constructs an ensemble of randomly generated binary trees, referred to as isolation trees (iTrees). For each tree, a feature is selected randomly, and a random split value is chosen within the range of that feature. This recursive partitioning continues until individual observations are isolated. Because anomalous data points tend to lie in sparse regions of the feature space, they are typically separated from the rest of the data after only a few splits, resulting in shorter path lengths within the tree structure. In contrast, normal observations require more partitions to become isolated and therefore exhibit longer average path lengths [44].

Formally, the anomaly score for an observation  $x$  in a dataset of size  $n$  is defined in the original formulation as:

$$s(x, n) = 2^{-\frac{E(h(x))}{c(n)}} \quad (2.18)$$

where  $h(x)$  denotes the path length of observation  $x$  in a given isolation tree,  $E(h(x))$  represents the expected path length averaged across the ensemble, and  $c(n)$  is the average path length of unsuccessful searches in a binary search tree, approximated as:

$$c(n) = 2H(n-1) - \frac{2(n-1)}{n} \quad (2.19)$$

with  $H(i) \approx \ln(i) + 0.577$  representing the harmonic number [48].

In this theoretical formulation, the anomaly score ranges between 0 and 1, where values approaching 1 indicate strong anomalies and values near 0 correspond to normal observations.

## 2.4. ANOMALY DETECTION AND EXPLAINABLE MACHINE LEARNING IN STRUCTURAL MONITORING

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In practical implementations, such as in the scikit-learn library [50], anomaly scores are provided as continuous values that may be positive or negative. A decision threshold, often set to zero, is applied to classify observations as anomalous or normal. This threshold can be adjusted depending on the monitoring objectives and desired sensitivity.

Isolation Forest presents several advantages for structural monitoring applications. First, it does not require labeled anomalous data, which are typically scarce in SHM scenarios. Second, it is computationally efficient and scalable to large datasets. Third, it can handle high-dimensional feature spaces without making strong distributional assumptions [47, 49]. These properties make it well suited for analyzing displacement-related features derived from PS-InSAR time series, where explicit damage labels are unavailable and structural anomalies may manifest as subtle deviations from dominant displacement trends.

### 2.4.3 EXPLAINABLE ML (SHAP)

While anomaly detection algorithms such as Isolation Forest can identify unusual structural behavior, interpreting these results in an engineering context remains a critical challenge. In safety-critical domains such as bridge monitoring, simply labeling a measurement as “anomalous” is not sufficient. Engineers must understand why a point has been classified as abnormal and which features contribute most to that decision. This requirement has motivated the growing interest in explainable machine learning (XML) methods within structural health monitoring [51, 52].

Many machine learning models, particularly ensemble and tree-based methods, are often considered “black-box” approaches because their internal decision processes are not directly interpretable. Although Isolation Forest provides anomaly scores, it does not inherently explain the relative contribution of individual features to a given prediction. In structural applications, this lack of interpretability may reduce trust in automated monitoring systems and limit their adoption in practice.

## 2.5. CHAPTER SUMMARY

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One widely adopted framework for model interpretability is SHAP (SHapley Additive ex-Planations), which is grounded in cooperative game theory [53]. SHAP assigns each feature a contribution value that quantifies its influence on the model output for a specific observation. These contributions are computed in a way that satisfies desirable theoretical properties such as consistency and local accuracy. As a result, SHAP enables both global interpretation (understanding overall feature importance across the dataset) and local interpretation (explaining why a specific observation was flagged as anomalous).

In the context of PS-InSAR displacement monitoring, explainability plays an important role. Displacement features derived from satellite time series may include velocity trends, seasonal amplitudes, residual components, or stability indicators. When an anomaly detection algorithm identifies a point as unusual, SHAP analysis can help determine whether the anomaly is driven by abnormal velocity evolution, irregular seasonal behavior, or instability in phase quality. This interpretability enhances engineering insight and supports informed decision-making.

The integration of anomaly detection with explainability therefore addresses two complementary objectives: automated identification of unusual structural behavior and transparent interpretation of the underlying drivers. For infrastructure monitoring, where decisions may affect maintenance strategies and public safety, such transparency is particularly important.

## 2.5 CHAPTER SUMMARY

This chapter has presented the theoretical and methodological foundations underlying the research conducted in this thesis. First, the principles of structural health monitoring and data-driven damage detection were discussed, highlighting the role of deep learning models in analyzing structural response signals. Subsequently, the geometric and signal-processing foundations of InSAR and PS-InSAR were introduced, together with their applications and limitations in bridge displacement monitoring. Finally, anomaly detection and explainable machine learning methods were reviewed, establishing their relevance for analyzing displacement time series in scenarios where labeled damage data are unavailable.

## 2.5. CHAPTER SUMMARY

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Together, these components form the conceptual basis for integrating satellite-based displacement monitoring with data-driven anomaly detection. While prior studies have addressed deep learning for structural response analysis and PS-InSAR for deformation monitoring separately, fewer efforts have systematically combined these approaches with interpretable anomaly detection for bridge assessment. The following chapters build upon the foundations presented here to develop and evaluate such an integrated framework.

# CHAPTER 3

## DAMAGE DETECTION FOR A CANTILEVERED STEEL I-BEAM THROUGH DEEP LEARNING METHODS: LSTM, MULTIVARIATE TIME-SERIES TRANSFORMER AND LSTM-BASED AUTOENCODER<sup>1</sup>

### 3.1 ABSTRACT

The structural integrity of steel trusses and I-beams is of vital importance for preventing steel bridges' potential collapse when subjected to extraordinary forces. Thus, identifying damages of I-beams, which cannot be noticed through usual inspections, based on their measured response, would enable early damage detection, and would trigger the necessary mitigation measures, to restore the structural integrity of the bridge. The current investigation built a vast database of structurally damaged cantilever I-beams, openings of various degrees and locations were placed along the beam to emulate reductions in stiffness. Both damaged and undamaged I-beams were modelled using Abaqus software, facilitated by Python scripting. Three deep learning algorithms were trained, validated and tested with the healthy and damaged I-beam cases: the Long Short-Term Memory (LSTM), LSTM-based autoencoder, and Multivariate Time-series Transformers (MTT), for which the input data consisted of acceleration responses recorded at specific points on the top flange of both undamaged and damaged I-beams subjected to harmonic dynamic loads. To enhance better adaptation for field monitoring data, random normal noise was introduced into the acceleration responses before running the ML damage identification algorithms. The three algorithms showed exceptional ability to accurately distinguish between damaged and undamaged I-beams. Furthermore, identifying the location of the damage on the beam was carried out by LSTM and MTT algorithms which revealed the best accuracy for damage localization. Finally, a comparative analysis of the three algorithms was conducted to clarify the optimal quantity of data points required to attain reliable results.

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<sup>1</sup>This chapter is based on the following published article: Sadeghian, E., and Dragomirescu, E. (2025). "Damage detection for a cantilevered steel I-beam through deep-learning methods: LSTM, multivariate time-series transformer, and LSTM-based autoencoder." *Journal of Computing in Civil Engineering*, 39(2), 04025003.



## 3.2 INTRODUCTION

Steel I-beams are essential structural elements for bridge orthotropic steel decks, that provide support and structural stability. If their strength and structural integrity are affected over time, due to potential corrosion, cracks or fatigue as they are subjected to extraordinary types of loads, such as earthquakes, collisions or others, these can lead to rapid collapse of the entire bridge structure, as noticed recently [54]. To ensure the safety and longevity of these structures, it is crucial to conduct regular inspections to assess their structural condition. Traditional inspection methods, such as visual inspections and non-destructive testing, are valuable tools and they have been used for many years, however, they have limitations in terms of accuracy and efficiency, mainly due to the inaccessibility of the inspected element, difficulty in detecting the internal damage, inability to detect dynamic changes and extreme weather conditions, among others. Recent advances in artificial intelligence (AI) and machine learning (ML) algorithms have revolutionized the investigation methodologies involving large amounts of data, such as sensor readings, images, and videos, to identify patterns and anomalies that may indicate damage or deterioration in structures and beams [55–66]. The novel application of ML algorithms allows engineers to detect structural problems earlier and with greater accuracy, thus reducing the risk of costly and potentially catastrophic failures of bridges and buildings. Some of the AI-based techniques used for structural condition assessment can be used in conjunction with traditional inspection methods, such as visual inspections and non-destructive testing, to provide a more comprehensive and accurate assessment of the beams' condition [67–69].

Recent studies in structural damage detection using artificial intelligence (AI) and machine learning (ML) developed an approach for condition assessment of suspension bridges using Deflection and temperature data [70], by considering the stiffness reduction in the bridge cables as deflection-sensitive damage. The damage was modelled for the investigated bridge by reducing the cross-sectional area of the cables and the LSTM deep learning algorithm was employed for predicting the bridge deck deflections using temperature and deflection time-series data as input. The authors found that the proposed method can identify and locate the deflection-sensitive

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damage in a suspension bridge, however, the LSTM could not identify the type of damage. [71] proposed an Anomaly Detection Method for a long-span suspension bridge based on an LSTM network with acceleration data as the input. The feasibility of the method has been verified by conducting two case studies: 1) finite element simulation, and 2) comparison with Structural Health Monitoring (SHM) collected from a real suspension bridge. Although the proposed method could identify the anomalies, these anomalies of the SHM data were either caused by abrupt changes in the structure's performance and external load, or by faults of the sensors themselves. Further studies need to effectively distinguish these two types of anomalies. [72] investigated a crack identification method by using a commercial UAV (unmanned aerial vehicle) with a high-resolution vision sensor in an aging concrete bridge. The thickness and length of cracks formed on the surface of the concrete structure were identified via Region Convolutional Neural (R-CNN)-based transfer learning. When tested on an aging bridge, it showed that the UAV-based bridge inspection system could be considered as a promising strategy. [73] proposed global and partial bidirectional long short-term memory (BiLSTM) models to establish a relationship between girder vertical deflection (GVD) and the cable tension of a cable-stayed bridge. The authors concluded that the BiLSTM algorithm can predict the cable tension of a cable-stayed bridge based on the GVDs in the presence of traffic volume and noise level, with high accuracy in both global and partial models. Despite the advantages of using AI in the condition assessment of structures. Machine learning algorithms have shown significant potential in automating the process of operational modal analysis and damage detection. [74] demonstrated the efficacy of ML in SHM applications, particularly for masonry arch bridges, by employing a combination of ML techniques and operational modal analysis. [75] highlighted the application of Extreme Function Theory (EFT) for damage detection in bridge monitoring. Their research underscores the advantages of EFT over traditional methods, particularly in reducing false positive rates and enhancing damage sensitivity. The review by [76] provides a comprehensive comparison of various SHM techniques, illustrating the benefits and limitations of frequency-based versus mode shape-based damage detection methods. The study emphasizes the need for integrating multiple data sources and advanced statistical methods to improve the accuracy and reliability of SHM systems. However, the effects of environmental variability conditions pose significant challenges

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to SHM, affecting early damage detection, localization, and quantification. Recent advancements in Structural Health Monitoring (SHM) have introduced innovative methods to address environmental variability. [77] compare four machine learning algorithms, auto-associative neural network (AANN), factor analysis (FA), Mahalanobis squared distance (MSD), and singular value decomposition (SVD), for structural damage detection under varying operational and environmental conditions. Using a three-story frame structure, they found AANN and MSD excel in true damage detection, while FA and SVD minimize false positives. The study emphasizes the importance of robust data normalization, with MSD being the preferred algorithm due to its simplicity and effective performance. [78] enhance feature extraction for SHM using time series modelling and unsupervised learning, improving order determination with the Box-Jenkins methodology. Validated on a concrete beam and experimental frame, the method accurately detects early damage using Andrews plot, k-means, and GMM clustering. [79] introduce a probabilistic self-clustering method using semi-parametric extreme value theory for structural health monitoring, effectively addressing variability and showing superior damage detection accuracy on the Z24 and Yonghe Bridges. In another study, [80] propose a multi-task unsupervised learning method for continuous bridge monitoring, using DBSCAN, spectral clustering, and empirical measures for anomaly detection. Validated on the Z24 and KW51 bridges, this method proves to reduce the false positives and negatives, offering accurate early damage detection under environmental changes.

Despite the promising AI and ML techniques, previous studies have highlighted several limitations and gaps, some of which this research aims to address. Many existing methods struggle with the scalability and generalization of the models, often requiring large amounts of labeled data that are not always available in real-world engineering situations. Additionally, the interpretability of AI models remains a significant challenge, as they are frequently viewed as "black-box" solutions with limited transparency regarding their decision-making processes. Furthermore, previous research has often focused on detecting the presence of damage without addressing the localization and severity of the damage within the structure [67–69]. The current study seeks to fill these gaps by developing a comprehensive approach that not only detects the presence of structural damage, but also accurately localizes it along the length of an I-beam. Our study integrates advanced deep learning techniques (LSTM and Multivariate Transformer models) with

### 3.3. STEEL I-BEAM MODEL AND THE TRAINING DATABASE

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numerical simulations of I-beam damage under dynamic loading conditions. It uniquely employs GridSearchCV to automatically optimize hyperparameters, considering dynamic responses for better model performance. The scalable methodologies can be adapted to various structures, providing a robust foundation for future structural health monitoring research.

Overall, AI-based damage identification and structural condition assessment offer significant advantages over traditional methods, including faster and more accurate detection of damage, reduced risk of human error, and increased safety and reliability of structures. As AI technology continues to advance, it is expected to play an increasingly important role in the field of structural engineering. Therefore, understanding the details of the machine learning algorithms enhances interpretability, allowing engineers to work with the results generated by AI models. In this paper, the efficiency of three deep-learning techniques (LSTM, Transformer, LSTM-based autoencoder) in damaged detection of a cantilevered beam using acceleration data from the beam is investigated. **A comprehensive overview of deep learning algorithms employed in this thesis is provided in Section 2.2.**

### 3.3 STEEL I-BEAM MODEL AND THE TRAINING DATABASE

Testing the performance of machine learning algorithms on basic structural components such as I-beams is crucial for comprehending their results and efficiency in real-world applications. Thus in the current study an IPE 360 cantilever I-beam of 2m length made of steel with a material density of  $7800 \text{ kg/m}^3$ , Poisson ratio of 0.28, and module of elasticity of 200 GPa was analyzed. The finite element model (FEM) of the beam, created in the Abaqus software, was used for generating the input data for the deep learning networks. Vertical acceleration response of the beam under a dynamic load, which is extracted from nine points through the center line of the top flange of the beam as it can be seen in Fig. 3.1, recorded at five seconds with a time step of 0.1 seconds, was used as input data to deep learning algorithms. In the FEM model, the I-beam was fixed at one end and was free at the other end (cantilevered beam), while for the mesh, C3D10, C3D15 and C3D20 element types, as provided by Abaqus, were employed. The load

### 3.3. STEEL I-BEAM MODEL AND THE TRAINING DATABASE

was chosen as the dynamic pressure acting on the top flange, with amplitudes varying linearly from zero to one in five seconds. It is worth noting that the explicit solver was carried out for the dynamic analysis. Initially, several cases were run with the undamaged I-beam. However, for the purpose of assessing the structural condition of the beam using the deep learning algorithms, several damaged beam scenarios were modelled as well and data for the same nine nodes on the top flanges were collected for training the deep learning network.

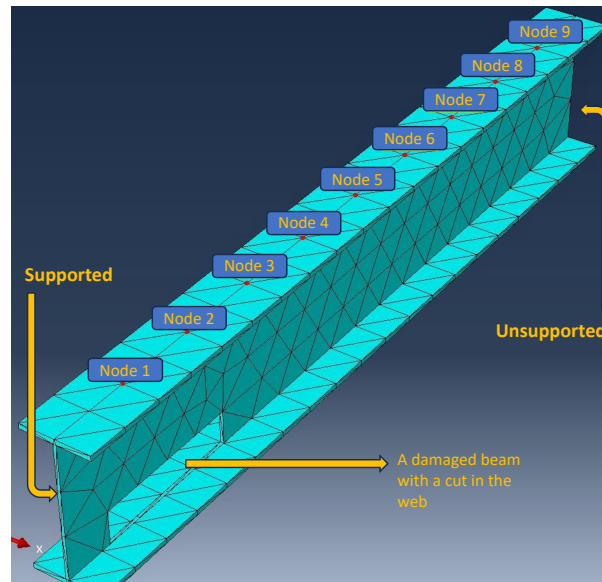


Figure 3.1: Nodes location on a damaged beam for extraction of the beam response.

Damages were applied to the beam to replicate the corrosion identified by field observations conducted by [81] for a total of 808 I-beams used in steel bridges and classified several corrosion patterns based on the thickness loss, damage location and opening size. For the current research, the main N2 and M4 corrosion patterns were adapted from [81], by reducing the cross-sectional area of the beam and thus simulating a stiffness reduction in the I-beam and by creating openings of various lengths (100 mm to 450 mm) and widths (25% to 100% of the bottom flange width), along different sections of the I-beam, as shown in Fig. 3.2.

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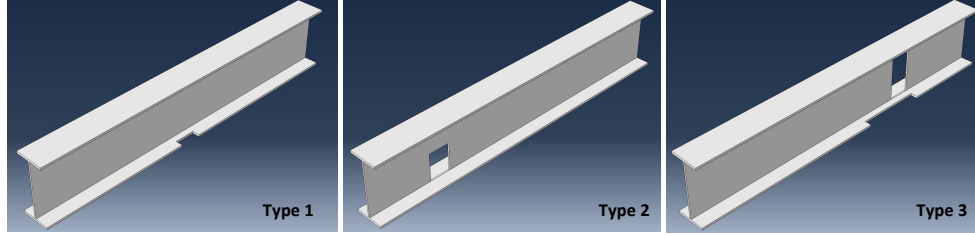


Figure 3.2: Damage types in the beam.

These openings were strategically placed on four regions along the length of the beam at the bottom flange (damage type 1), on the web (damage type 2), and at both bottom flange and web simultaneously (damage type 3), spanning the entire length of the beam (Fig. 3.2). By simulating such damages, we aim to study their effects on the structural behavior and performance of the beam, including reduced load-carrying capacity, altered structural stiffness, changes in the mode of failure, and increased stress concentration. This approach ensures that the simulated damage scenarios are not only representative of common structural issues but also provide a comprehensive dataset for analyzing the performance of damage detection algorithms. In total, 1443 data samples were generated, comprising 1151 damaged and 292 undamaged samples. Notably, damage samples were equally generated, therefore at each quarter of beam length (Fig. 3.3), about 288 damaged samples were created.

The selection of 1443 samples was primarily based on ensuring a significant proportion of damaged samples (ratio 4:1) to enable effective learning from diverse damage scenarios. This reflects realistic conditions where damage is more frequent while maintaining enough undamaged samples for accurate classification. The sample size balances the need for a large dataset with the practical limits of computational resources. The 1151 damaged samples represent three damage types (bottom flange, web, and both) at four beam quarters in various sizes and locations, ensuring the model generalizes well. The chosen sample size also ensures statistical significance in performance metrics. Each data sample was organized into a  $51 \times 9$  matrix, where the columns represented the nine specific data points, and the rows corresponded to the extracted acceleration data over a duration of five seconds, with a time-step of 0.1 second. Creating such

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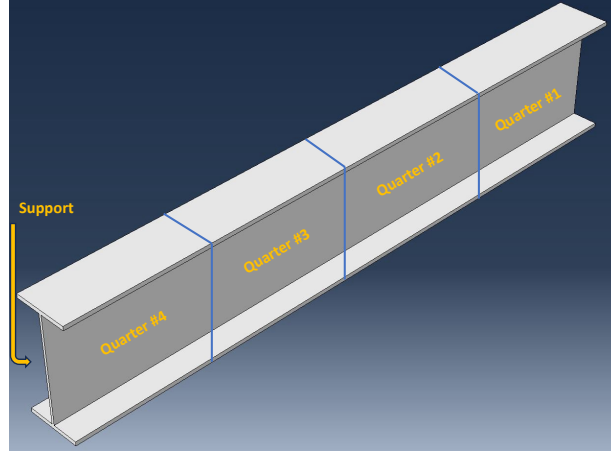


Figure 3.3: Quarters location in beams for purpose of labelling the data.

a large data set using Abaqus software proved to be a time-consuming process, even for a basic I-beam structure. To address this challenge, data generation and extraction process are automated using Python scripting within the Abaqus environment, streamlining the otherwise laborious task. Figure 3.4 represents the acceleration time-history responses of the I-beams with different damage conditions, as depicted in Fig. 3.2, recorded for the nine data points corresponding to each node introduced in Fig. 3.1 for all four beam quarters (Fig. 3.3). The workflow depicted in Fig. 3.5 outlines each step from initial I-beam modeling to the final damage detection phase, ensuring a systematic and thorough approach.

## 3.4 EFFICIENCY OF DEEP LEARNING ALGORITHMS FOR I-BEAM STRUCTURAL ASSESSMENT

The outcomes of evaluating the beam's structural condition using the three algorithms, LSTM, Multivariate Time-series Transformer and LSTM-based autoencoder, along with the efficiency of each algorithm, are outlined below. Each of the examined algorithms was tested with different sets of hyperparameters and architecture, such as the number of layers and units, learning rate,

### 3.4. EFFICIENCY OF DEEP LEARNING ALGORITHMS FOR I-BEAM STRUCTURAL ASSESSMENT

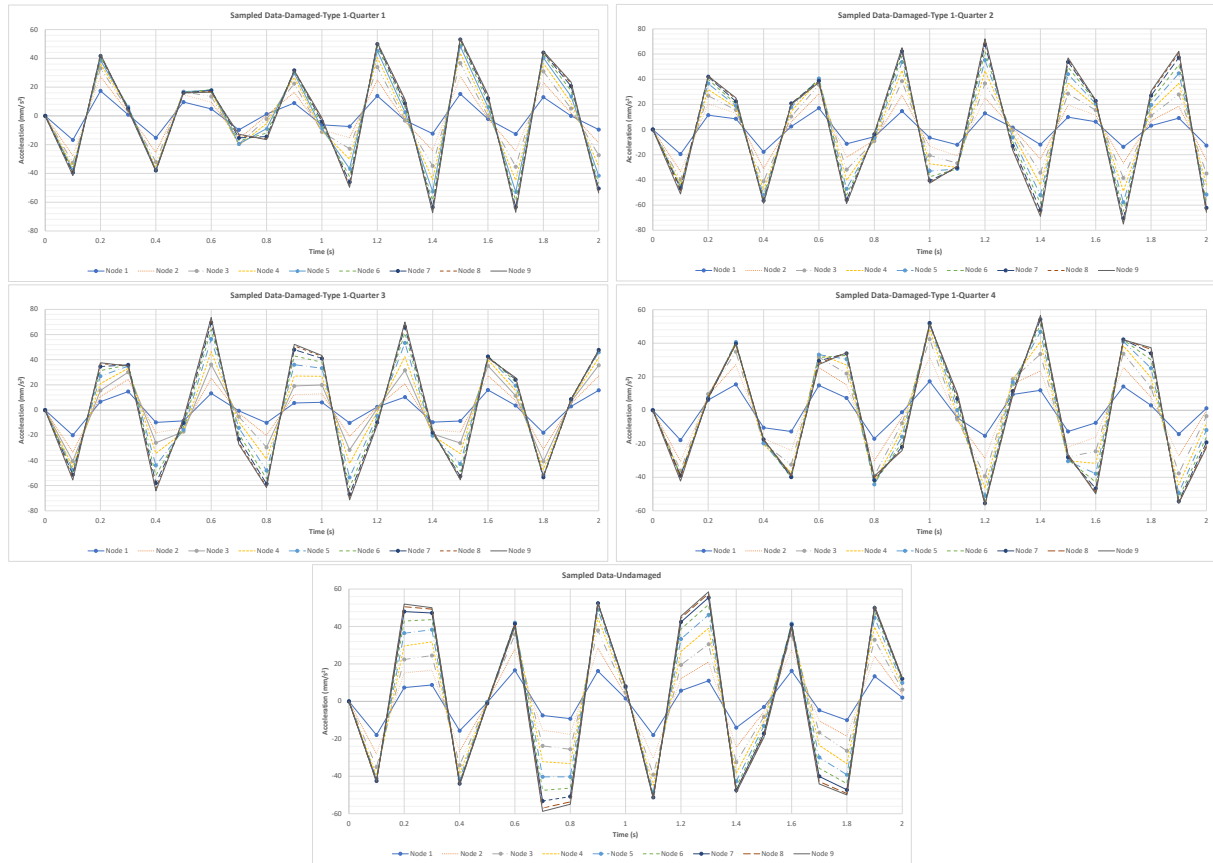


Figure 3.4: Acceleration response of undamaged and damaged beams recorded for the nine data points as the raw input to the networks.



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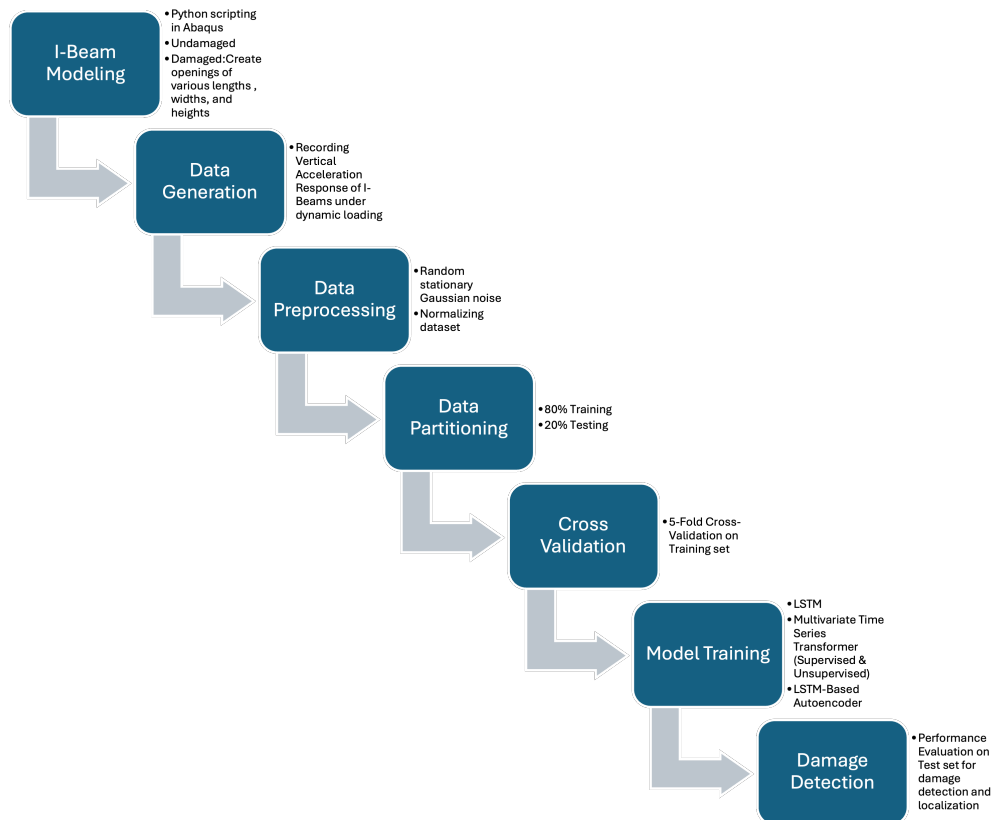


Figure 3.5: Workflow for Damage Detection in I-Beam models.

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activation function, batch size, and epoch. The most effective combination of these parameters was quantified in detail to provide the efficiency of the employed methods. Furthermore, the research delved into determining the optimal number of data points necessary to identify the damage on the I-beam. This investigation involved considering different quantities of data points on the beam, specifically nine, six, and four nodes.

#### 3.4.1 EFFICIENCY OF THE LSTM ALGORITHM FOR DAMAGE DETECTION

As mentioned in the previous section, a total of 1443 I-beam response samples were generated, while a random stationary noise, with zero mean and standard deviation of one, was added to the entire dataset to consider the effect of noise in the data extraction process to better reflect the SHM data. Using only one level of normal noise was a limitation of the current research. In the second phase, the project will focus on extending the noise robustness evaluation of the proposed methodologies. By introducing multiple levels of white Gaussian noise with varying standard deviations, the robustness of the models to different noise intensities will be thoroughly assessed. This will provide a clearer understanding of the algorithms' capabilities and limitations in real-world SHM applications, where noise levels can vary significantly. In addition, based on the min-max scaling method, the dataset was scaled to the range of  $[-2, 2]$ . Normalization helps to standardize the input data, reducing the risk of exploding or vanishing gradients during training, which is a common problem in deep learning models [82]. Scaling the data to a specific range, such as  $[-2, +2]$ , ensures that all features contribute equally to the learning process, preventing any single feature from dominating the training due to its larger magnitude. This range amplifies data variability, making subtle variations more pronounced, which improves the model's ability to distinguish between different damage types and severities. Additionally, this scaling is beneficial when using activation functions like the hyperbolic tangent ( $\tanh$ ), which compresses inputs within a range of  $[-1, +1]$ , allowing for better gradient flow and faster convergence. Numerical experiments in our study showed that scaling to  $[-2, +2]$  resulted in improved convergence rates and higher accuracy metrics compared to unscaled data, optimizing the model's learning process and overall performance. The way that the data is generated helps not only in identifying the

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presence of damage on the I-beam, but also it estimates the location of the damage along the length of the beam, since we are dealing with a localization problem. For this reason, five damage classes (DC) were defined and samples were labelled accordingly (Table 3.1). The first class separates the undamaged beam data from the damaged one, while damage classes (DC) 2 to 5 estimate in which quarter of the beam the damage happened. Damage class 2 represents the damage that occurred at Quarter 1, located at the unsupported end of the beam, while damage class 5 represents the damage that happened at Quarter 4 near the support of the I-beam. Damages in Classes 3 and 4 were concentrated within the mid-section Quarters 2 and Quarters 3 of the beam. To train and evaluate the deep learning models, the dataset was partitioned into two main subsets: 80% was allocated for training, and 20% was reserved for testing. During the training phase, a 5-fold cross-validation approach was employed within the training data. Training part of the data (1155 samples) was used to train the model. The training based on the data in this set served for learning the patterns and relationships within the data. Test set (288 samples) was held out and was employed only for the final evaluation of the model. It provides an unbiased estimate of the model's performance for newly unseen data. The test samples were selected such that each class contained an equal number of 57 test samples and each class encompassed the full range of relative damage types and intensities. Within the 80% training data (1155 samples), a 5-fold cross-validation approach was employed to further divide the data. The training data was randomly divided into five equal-sized folds. In each of the five iterations, one-fold was used as the validation set, and the remaining four folds were used for training the model. This process was repeated five times, ensuring that each fold served as the validation set exactly once, thus allowing for robust hyperparameter tuning and model validation. Also, the benefit of using the 5-fold cross-validation consists in mitigating overfitting, as the model's performance is evaluated on multiple validation sets and therefore it provides a more reliable estimate of the model's stability across different data subsets. After completing the 5-fold cross-validation, the model's performance was assessed on the 20% holdout test data. This test set was not used in any of the training or validation phases, ensuring an unbiased evaluation of the model's generalization capability to new, unseen data. Based on the available dataset, the 80% training and 20% test split

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is a common practice that balances having enough data for training while reserving a substantial portion for unbiased testing (Fig. 3.6).

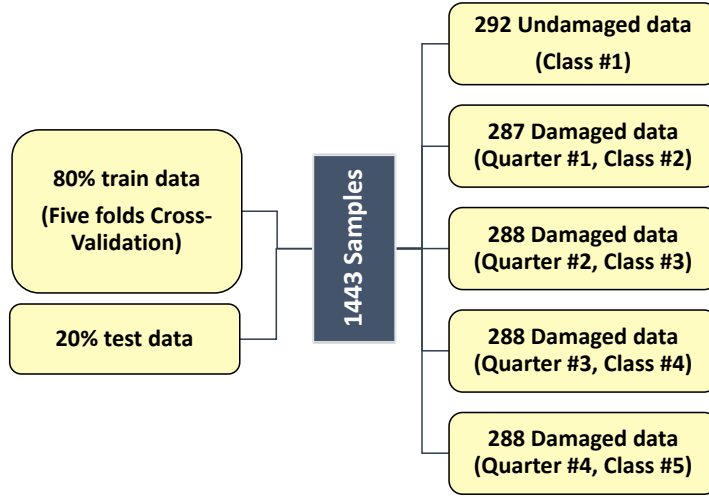


Figure 3.6: Data distribution and labelling for training and testing in LSTM and Transformer network.

In the exploration of the LSTM model configurations, three distinct architectures were evaluated. The first architecture comprises a two-layer configuration: the initial layer is an LSTM layer with 128 units, followed by a subsequent dense layer containing five units with a softmax activation function. The second architecture involves a composition of two LSTM layers, each with 128 and 64 units respectively, with a dense layer acting as the output layer. Lastly, the third architecture includes a total of three layers: an initial LSTM layer with 128 units followed by two subsequent dense layers with 64 and 32 units respectively. To transition from a regression model (classic LSTM) to a classification model, LSTM layer was employed to capture temporal dependencies in the time-series acceleration data collected from the I-beam. The LSTM layer processes the data and outputs a sequence of hidden states encoding information about the input sequence. These rich temporal features are then passed to a Dense (fully connected) layer, which converts them into a format suitable for classification. The Dense layer, containing five units corresponding to the five damage classes, uses a softmax activation function to output a probability distribution over the classes. This combination leverages the LSTM's ability to capture sequential

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dependencies and the Dense layer's capability to classify the extracted features, ensuring accurate damage detection and localization. Each of the three architectures of LSTM was used with the acceleration responses collected from 9 points, 6 points and 4 points along the beam, as input data to determine if the damaged class can be identified. Tables 3.1 to 3.3 show the precision, recall and the F1-score obtained for different numbers of acceleration responses on the beam (data points) for each architecture. In the context of classification tasks within machine learning, precision, recall, and the F1-score are critical metrics used to evaluate the performance of a model. Precision, also known as the positive predictive value, measures the proportion of true positives against all positive predictions made by the model, essentially capturing the model's accuracy in predicting positive instances. Recall, or sensitivity, assesses the proportion of actual positives that the model correctly identified, thus indicating the model's ability to detect positive instances. The F1-score provides a harmonic mean of precision and recall, offering a single metric that balances both. It is particularly useful when the class distribution is uneven, and it accounts for both the model's precision and recall. For each case, different combinations of hyperparameters for the LSTM model were considered, and from all the models, only the results related to the best model with specific hyperparameters are presented.

As it can be noticed in Tables 3.1 to 3.3 and Fig. 3.7, the LSTM algorithm with type 1 architecture with sets of 9, 6 and 4 data points showed the best results in terms of precision and F1-score, especially for Damage Classes 1 and 5, which correspond to the general damage on the I-beam and I-beam with damage located near the support (Quartile 4). For Class 2, when the damage was located near the free end of the I-beam (Quartile 1) the precision of identifying damage with LSTM algorithm decreased to almost half (in some cases it is zero or near zero), for all architectures and data sets. These findings demonstrate that, overall, the LSTM model displays exceptional accuracy achieving a flawless 100% prediction in identifying the existence of damage on an I-beam (Class one). Remarkably, this LSTM model proves adept at detecting the existence of damage in the beam even with a sparse input dataset. Moreover, across various scenarios, particularly with 9 data points, the model exhibits favourable performance metrics for Damage Classes 4 and 5. This implies the LSTM's ability to effectively pinpoint damage locations situated near the beam's midsection and close to the support. Conversely, for Damage

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Classes 2 and 3, the model's effectiveness in identifying damage near the unsupported end of the beam decreased with the decrease in the number of data points considered.

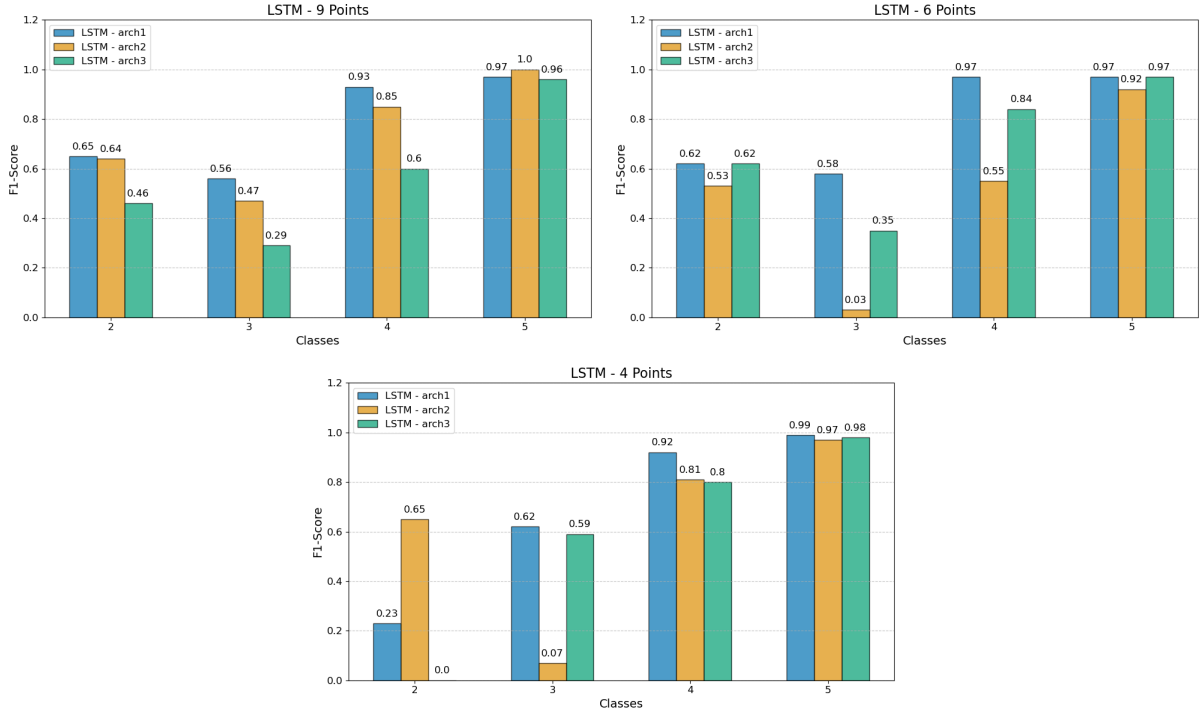


Figure 3.7: F1-score comparison of different LSTM architectures with nine, six, and four data points for each class.

Notably, among all configurations, the LSTM model utilizing architecture 2 and employing 9 data points yielded the highest average metrics for all classes (Table 3.2). The optimal hyperparameters, chosen among the 64 combinations, include a dropout rate of 0.2, a batch size of 16, 300 epochs, a learning rate of 0.001, and 128 and 32 LSTM units for the initial and secondary LSTM layers, respectively, thus resulting in a total learnable 91429 parameters, for which the training process is represented in Fig. 3.8. The Adam optimizer was used for training, and categorical cross-entropy was used as the loss function. The training process involved monitoring the loss and recall metrics, with early stopping criteria based on validation loss to prevent overfitting. The loss graph exhibits a declining trend with increasing the number of epochs, levelling off

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Table 3.1: Classification metrics of LSTM-architecture 1 damage detection model.

| Class   | No.<br>Samples | Precision |      |      | Recall |      |      | F1-score |      |      |
|---------|----------------|-----------|------|------|--------|------|------|----------|------|------|
|         |                | 9N        | 6N   | 4N   | 9N     | 6N   | 4N   | 9N       | 6N   | 4N   |
| Class 1 | 58             | 1.00      | 1.00 | 0.76 | 1.00   | 1.00 | 1.00 | 1.00     | 1.00 | 0.87 |
| Class 2 | 57             | 0.61      | 0.61 | 0.56 | 0.70   | 0.68 | 0.39 | 0.65     | 0.64 | 0.46 |
| Class 3 | 58             | 0.60      | 0.50 | 0.36 | 0.52   | 0.45 | 0.24 | 0.56     | 0.47 | 0.29 |
| Class 4 | 58             | 0.95      | 0.86 | 0.52 | 0.91   | 0.84 | 0.71 | 0.93     | 0.85 | 0.60 |
| Class 5 | 57             | 0.97      | 1.00 | 0.98 | 0.98   | 1.00 | 0.95 | 0.97     | 1.00 | 0.96 |
| -       | Avg            | 0.82      | 0.80 | 0.66 | 0.82   | 0.80 | 0.66 | 0.82     | 0.80 | 0.66 |

Table 3.2: Classification metrics of LSTM-architecture 2 damage detection model.

| Class   | No.<br>Samples | Precision |      |      | Recall |      |      | F1-score |      |      |
|---------|----------------|-----------|------|------|--------|------|------|----------|------|------|
|         |                | 9N        | 6N   | 4N   | 9N     | 6N   | 4N   | 9N       | 6N   | 4N   |
| Class 1 | 58             | 1.00      | 0.98 | 0.76 | 1.00   | 1.00 | 1.00 | 1.00     | 0.99 | 0.87 |
| Class 2 | 57             | 0.60      | 0.41 | 0.56 | 0.65   | 0.74 | 0.39 | 0.62     | 0.53 | 0.46 |
| Class 3 | 58             | 0.62      | 0.17 | 0.36 | 0.55   | 0.02 | 0.24 | 0.58     | 0.03 | 0.29 |
| Class 4 | 58             | 0.97      | 0.52 | 0.52 | 0.97   | 0.59 | 0.71 | 0.97     | 0.55 | 0.60 |
| Class 5 | 57             | 0.97      | 0.93 | 0.98 | 0.98   | 0.91 | 0.95 | 0.97     | 0.92 | 0.96 |
| -       | Avg            | 0.83      | 0.65 | 0.66 | 0.83   | 0.65 | 0.66 | 0.83     | 0.65 | 0.66 |

around epoch 300. Despite reaching a relatively low loss of approximately 0.5, there were instances of skewed misclassifications impacting certain damage classes. While the damage classes might be balanced overall in terms of the dataset's distribution, some classes experienced higher misclassification rates. To address this issue, a 5-fold cross-validation approach ensured model performance evaluation across multiple data subsets to mitigate bias. Additionally, precision, recall, and F1-score metrics, alongside overall accuracy, were used to comprehensively assess the model's performance for each damage class. Even though the LSTM model has high recall overall, it might perform less efficient for specific classes, leading to a higher loss due to misclassifications in those classes. Therefore, although the total loss of 0.5 during training might seem elevated, it does not undermine the model's learning capacity. On the other hand, the recall

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Table 3.3: Classification metrics of LSTM-architecture 3 damage detection model.

| Class   | No.<br>Samples | Precision |      |      | Recall |      |      | F1-score |      |      |
|---------|----------------|-----------|------|------|--------|------|------|----------|------|------|
|         |                | 9N        | 6N   | 4N   | 9N     | 6N   | 4N   | 9N       | 6N   | 4N   |
| Class 1 | 58             | 1.00      | 1.00 | 1.00 | 1.00   | 1.00 | 1.00 | 1.00     | 1.00 | 1.00 |
| Class 2 | 57             | 0.57      | 0.50 | 0.00 | 0.14   | 0.91 | 0.00 | 0.23     | 0.65 | 0.00 |
| Class 3 | 58             | 0.49      | 1.00 | 0.44 | 0.86   | 0.03 | 0.93 | 0.62     | 0.07 | 0.59 |
| Class 4 | 58             | 0.95      | 0.78 | 0.89 | 0.90   | 0.84 | 0.72 | 0.92     | 0.81 | 0.80 |
| Class 5 | 57             | 0.98      | 0.93 | 0.97 | 1.00   | 1.00 | 1.00 | 0.99     | 0.97 | 0.98 |
| -       | Avg            | 0.78      | 0.76 | 0.73 | 0.78   | 0.76 | 0.73 | 0.78     | 0.76 | 0.73 |

graph depicts an increasing trend as epochs progress, stabilizing around epoch 300, representing a reasonable progression in model performance.

#### 3.4.2 EFFICIENCY OF THE MULTIVARIATE TIME-SERIES TRANSFORMER ALGORITHM FOR DAMAGE DETECTION

Two approaches were considered when implementing the Multivariate Time-series Transformer for damage identification of the I-beam the Supervised MTT and the Unsupervised MTT. Data preprocessing and training and testing processes for damage detection of the beam using the Supervised MTT are the same as the LSTM algorithm, however for the task of Unsupervised MTT implementation, a portion  $r$  of each data point sequence masked in the input independently is required, such that across each data point sequence, time segments of mean length  $l_m$  are masked, each followed by unmasked segment of mean length  $l_u = \frac{1-r}{r}l_m$ . In the output, the model tries to predict the full uncorrupted input sequences; however, only the predictions on the masked values are considered in the mean squared error loss [21]. Thereafter, the pre-trained model would be used to localize the damage in the beam.

In accordance with the findings detailed in Tables 3.4, and 3.5 and Fig. 3.9 which reflect the efficiency parameters for the Supervised and Unsupervised MTT, similar to the LSTM algorithm, the MTT models exhibit the capability to identify the presence of damage in the beam (Damage



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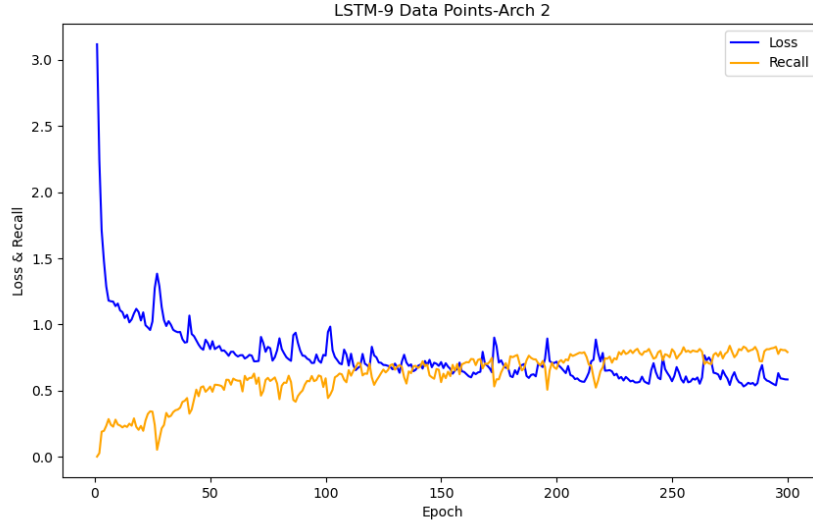


Figure 3.8: Loss and Recall vs epoch during training data for classification of damage using LSTM algorithm with architecture two and nine data points.

Class 1) even for lower number of data points within the test dataset. The performance metrics for the other damage classes demonstrate a slight improvement in both transformer algorithms compared to the LSTM algorithm across varying data point quantities. For damage class 5, when the damage is closest to the support, both Supervised and Unsupervised MTT performed very well, for all data points sets, however for the other Classes 2, 3 and 4, it was noticed that the Unsupervised MTT performed slightly better when decreasing the number of data points. Additionally, interpretation of loss and accuracy performances represented in Fig. 3.10 indicates that the transformer models exhibit accelerated learning rates during training compared to the LSTM algorithm. The optimal epoch for the supervised transformer occurs at epoch 32, boasting a loss of 0.34 and an accuracy of 83%, while the unsupervised transformer reaches its best epoch at epoch 12 with a loss of 0.29 and an accuracy of 86%. Notably, in the context of damage detection classification, the unsupervised time-series transformer exhibits approximately 2.5% higher metrics on average compared to the supervised counterpart. This enhancement is attributed to the unsupervised model's pre-training process, facilitating a faster training pace compared to

### 3.4. EFFICIENCY OF DEEP LEARNING ALGORITHMS FOR I-BEAM STRUCTURAL ASSESSMENT

the supervised model. The swift initial training of transformer models leads to an early decline in loss during the initial epochs. However, as these models encounter diverse data conditions, the loss exhibits a slight increase before stabilizing around epoch 300.

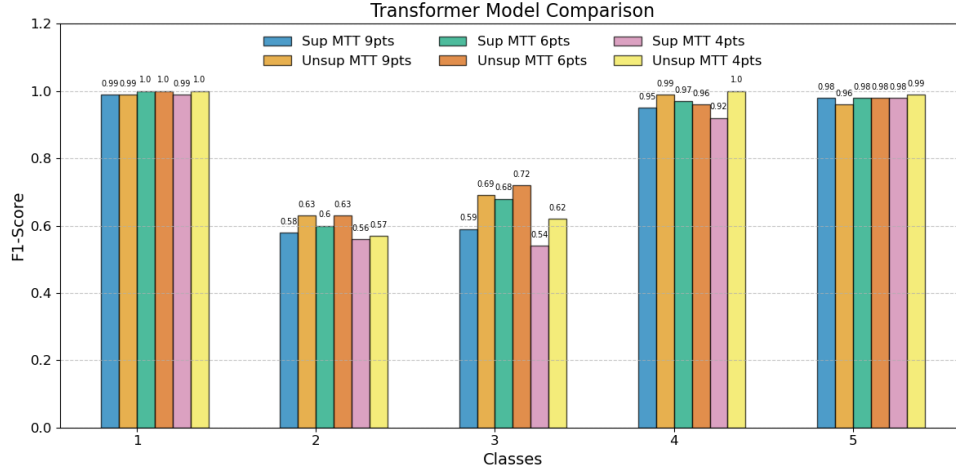


Figure 3.9: F1-score comparison of supervised and unsupervised MTT for different number of data points for each class.

Table 3.4: Classification metrics of supervised time-series transformer model.

| Class   | No.<br>Samples | Precision |      |      | Recall |      |      | F1-score |      |      |
|---------|----------------|-----------|------|------|--------|------|------|----------|------|------|
|         |                | 9N        | 6N   | 4N   | 9N     | 6N   | 4N   | 9N       | 6N   | 4N   |
| Class 1 | 58             | 0.98      | 1.00 | 0.98 | 1.00   | 1.00 | 1.00 | 0.99     | 1.00 | 0.99 |
| Class 2 | 57             | 0.63      | 0.67 | 0.57 | 0.54   | 0.54 | 0.54 | 0.58     | 0.60 | 0.56 |
| Class 3 | 58             | 0.57      | 0.62 | 0.54 | 0.60   | 0.74 | 0.53 | 0.59     | 0.68 | 0.54 |
| Class 4 | 58             | 0.91      | 0.97 | 0.90 | 1.00   | 0.97 | 0.95 | 0.95     | 0.97 | 0.92 |
| Class 5 | 57             | 1.00      | 0.98 | 0.98 | 0.96   | 0.98 | 0.98 | 0.98     | 0.98 | 0.98 |
| -       | Avg            | 0.82      | 0.85 | 0.80 | 0.82   | 0.85 | 0.80 | 0.82     | 0.85 | 0.80 |

The average metric outcomes for both supervised and unsupervised time-series transformer models manifest superior performance when six data points are employed as input features (Tables 3.4, 3.5 and Fig. 3.9. Optimal hyperparameters for both models encompass 3 encoder

### 3.4. EFFICIENCY OF DEEP LEARNING ALGORITHMS FOR I-BEAM STRUCTURAL ASSESSMENT

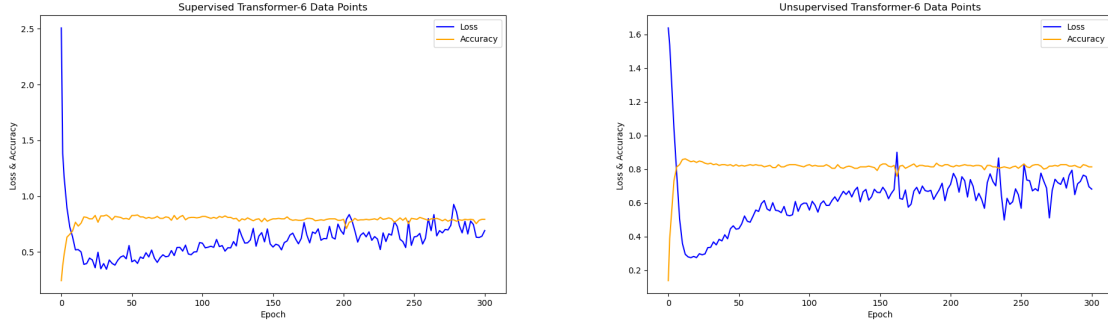


Figure 3.10: Loss and accuracy vs epoch during training data for classification of damage using Supervised and Unsupervised transformer algorithm with six data points as input.

Table 3.5: Classification metrics of unsupervised time-series transformer model.

| Class   | No.<br>Samples | Precision |      |      | Recall |      |      | F1-score |      |      |
|---------|----------------|-----------|------|------|--------|------|------|----------|------|------|
|         |                | 9N        | 6N   | 4N   | 9N     | 6N   | 4N   | 9N       | 6N   | 4N   |
| Class 1 | 58             | 0.98      | 1.00 | 1.00 | 1.00   | 1.00 | 1.00 | 0.99     | 1.00 | 1.00 |
| Class 2 | 57             | 0.70      | 0.76 | 0.60 | 0.56   | 0.54 | 0.54 | 0.63     | 0.63 | 0.57 |
| Class 3 | 58             | 0.64      | 0.65 | 0.59 | 0.76   | 0.80 | 0.65 | 0.69     | 0.72 | 0.62 |
| Class 4 | 58             | 1.00      | 0.94 | 1.00 | 0.98   | 0.98 | 1.00 | 0.99     | 0.96 | 1.00 |
| Class 5 | 57             | 0.96      | 0.98 | 1.00 | 0.96   | 0.98 | 0.98 | 0.96     | 0.98 | 0.99 |
| -       | Avg            | 0.85      | 0.86 | 0.84 | 0.85   | 0.86 | 0.84 | 0.85     | 0.86 | 0.84 |

blocks, each containing 8 multi-head attention layers, a feed-forward neural network comprising 256 units, and an embedding with a dimension of 128. Commonly set parameters for both models include a learning rate of 0.001, a batch size of 128, and an epoch count of 300, resulting in a total of 437509 learnable parameters. Fig. 3.11 illustrates the architectures of the LSTM and Transformer models with the highest performance used in this study. Noteworthy is the distinct setting for pretraining the unsupervised model, employing 700 epochs and a batch size of 32. The loss, accuracy, and precision versus epoch for both supervised and unsupervised tasks for six data points are visualized in the following figures. In addition to the discussed metrics, the ROC curves shown in Fig. 3.12 provide further insights into the performance of the three

### 3.4. EFFICIENCY OF DEEP LEARNING ALGORITHMS FOR I-BEAM STRUCTURAL ASSESSMENT

algorithms. The ROC curves compare the true positive rate against the false positive rate for each classifier, offering a clear visualization of their distinguishing power. The Unsupervised Transformer model, with 6 data points, achieved the highest AUC of 0.85, indicating superior performance in damage detection. The Supervised Transformer model also performed well with an AUC of 0.80, followed by the LSTM model with 9 data points, which achieved an AUC of 0.78. These results demonstrate the effectiveness of the Transformer models, particularly the unsupervised variant, in identifying structural anomalies with high accuracy.

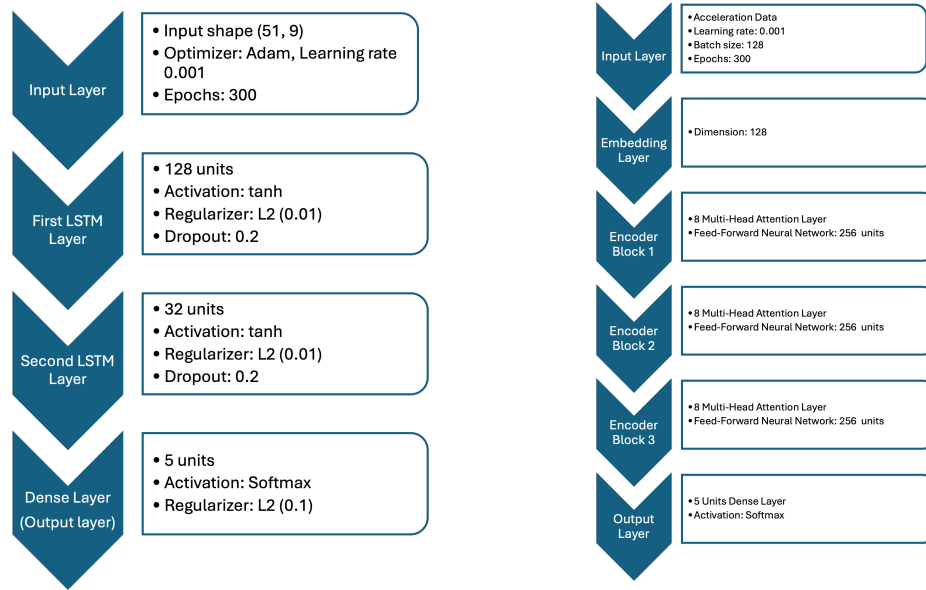


Figure 3.11: Model Architectures and hyperparameters for LSTM and Transformer Networks with highest performance.

#### 3.4.3 EFFICIENCY OF THE LSTM-BASED AUTOENCODER ALGORITHM FOR DAMAGE DETECTION

In implementing the noise injection technique, each undamaged sample underwent the generation of four noisy versions by introducing four sets of random normal noise with a noise factor of

### 3.4. EFFICIENCY OF DEEP LEARNING ALGORITHMS FOR I-BEAM STRUCTURAL ASSESSMENT

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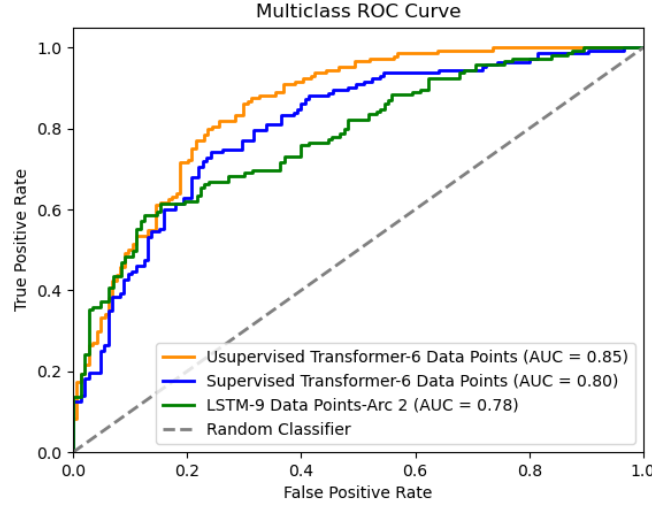


Figure 3.12: Multiclass ROC Curve for the LSTM and Transformer Models.

0.1 to the original sample. This augmentation strategy significantly expanded the undamaged dataset from 292 to 1460 samples. Additionally, all samples underwent scaling to optimize the model's training process. Subsequently, for model training, 80% (1168 samples) of the augmented undamaged dataset was utilized.

Following model training, the remaining 20% of the undamaged data, in conjunction with 230 damaged samples representing various types of damages previously generated, totalling 522 samples, was designated for evaluating the trained model's performance. The primary objective post-training was to ascertain the model's capability to reconstruct undamaged inputs with minimal error while exhibiting higher reconstruction errors for damaged inputs. A threshold for the reconstruction error was established, set as the median of all epoch losses plus three times the median absolute deviation (MAD) of all losses.

Figures 3.13 and 3.14 visually display the reconstructed signals for both a damaged and an undamaged input with four data points as input features. Notably, the results illustrate the algorithm's adeptness in flawlessly reconstructing undamaged inputs. This ability to accurately reconstruct undamaged inputs serves as a foundational aspect in predicting anomalous inputs

### 3.4. EFFICIENCY OF DEEP LEARNING ALGORITHMS FOR I-BEAM STRUCTURAL ASSESSMENT

based on higher reconstruction errors observed in damaged inputs relative to the established threshold.

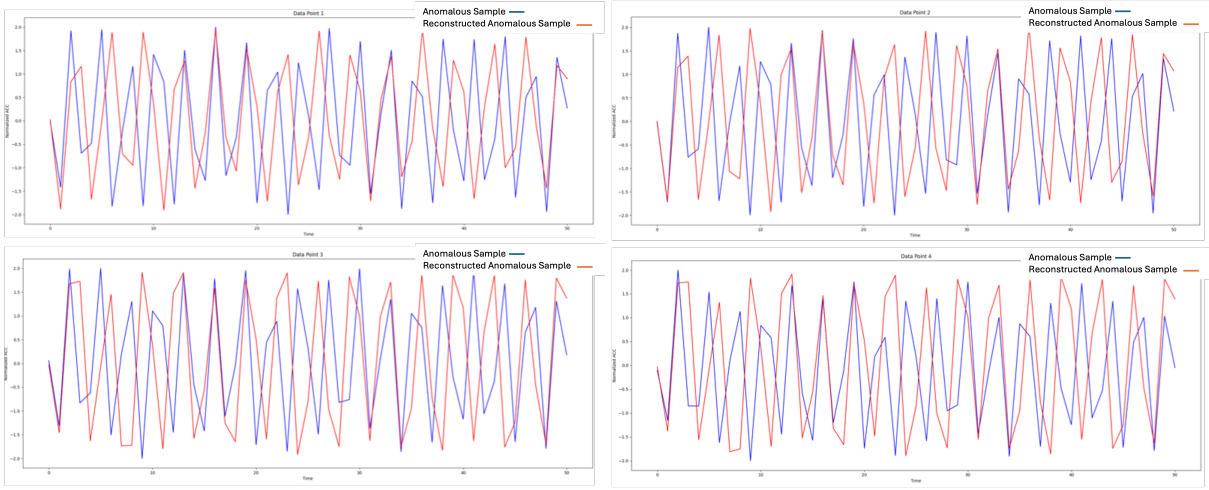


Figure 3.13: Reconstructed anomalous (damaged) sample versus the original damaged sample with four data points using the anomaly detection algorithm.

The graphs depicted in Fig. 3.15 exhibit the relationship between loss and epoch during the training phase across varying quantities of data points. The observed trend suggests that as the dataset size expands, the anomaly detection algorithm demonstrates improved and expedited training, achieving enhanced accuracy in reconstructing undamaged samples reliably. Remarkably, even when dealing with smaller quantities of data points, the algorithm showcases proficiency in identifying anomalies within damaged data by comparing them to undamaged beam responses. Despite the reduced dataset size, the algorithm retains its capability to discern these anomalies, emphasizing its resilience in detecting irregularities within the context of undamaged beam responses.

To provide a comparison of the algorithms' performance, Table 3.6 presents the precision, recall, F1-score, and overall effectiveness of the LSTM, Transformer, and LSTM-based Autoencoder algorithms. The LSTM algorithm demonstrated high precision and F1-scores for detecting general damage and damage near the support, but its effectiveness decreased for damage near

### 3.4. EFFICIENCY OF DEEP LEARNING ALGORITHMS FOR I-BEAM STRUCTURAL ASSESSMENT

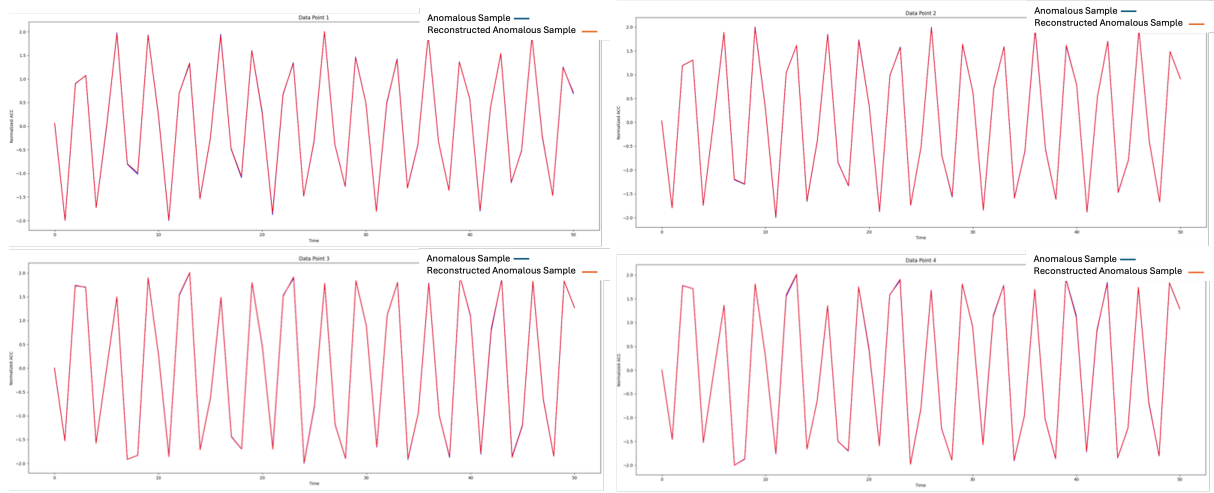


Figure 3.14: Reconstructed nonanomalous (undamaged) sample versus the original undamaged sample with four data points using the anomaly detection algorithm.

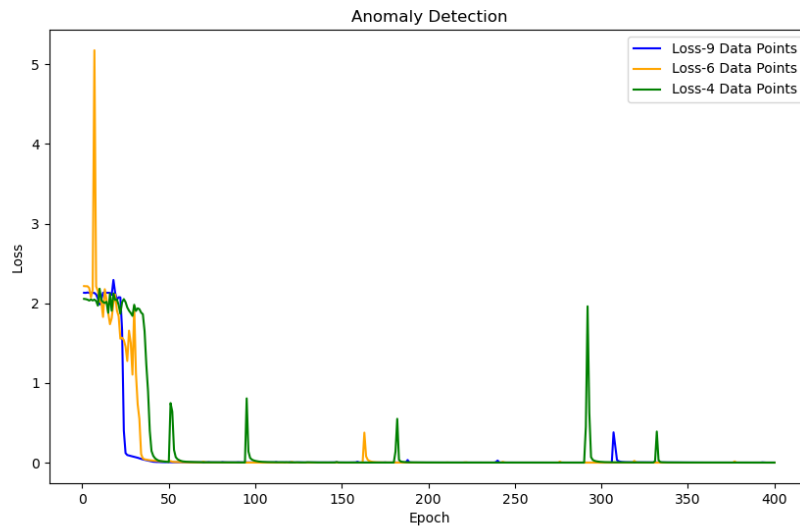


Figure 3.15: Loss vs epoch during training data for classification of damage using LSTM-based autoencoder algorithm with nine, six and four data points as input.

### 3.5. CONCLUSION

the unsupported end of the beam. The Transformer models, both supervised and unsupervised, showed robust performance across all damage types and locations, with the unsupervised variant performing slightly better with fewer data points. The LSTM-based Autoencoder algorithm, despite requiring augmentation due to a scarcity of undamaged samples, proved effective in detecting significant anomalies and severe damage, with improved accuracy and training efficiency as dataset size increased.

Table 3.6: Comparative Performance of LSTM, Transformer, and LSTM-based Autoencoder Algorithms.

| Algorithm              | Precision, Recall, and F1-Score                                                                                                                                            | Performance on Damage Types                                                         | Performance on Damage Locations                                                    | Effectiveness                                                                                                                                                                               |
|------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| LSTM                   | The LSTM algorithm, particularly architecture 1 with 9, 6, and 4 data points, achieved the best precision and F1-score for Damage Classes 1 and 5.                         | Effective for gradual damage detection; less effective for abrupt damage detection. | Effective for mid-span damage detection; less effective for edge damage detection. | Effective for identifying damage existence even with sparse input datasets. Performance decreases for Classes 2 and 3 as the number of data points decreases.                               |
| Transformer            | Transformer models successfully identified damage presence (Class 1) even with fewer data points. Other damage classes showed slight improvements compared to LSTM models. | Effective for both gradual and abrupt damage detection.                             | Effective for detecting damage across all locations.                               | Both supervised and unsupervised MTT models performed well for Class 5. Unsupervised MTT showed slightly better robustness with fewer data points for Classes 2, 3, and 4.                  |
| LSTM-based Autoencoder | The LSTM-based autoencoder required training using undamaged data. Data augmentation improved training reliability despite limited samples.                                | Effective for significant anomaly detection; less effective for minor anomalies.    | Effective for severe damage detection; less effective for minor damage detection.  | Demonstrated improved training efficiency and reconstruction accuracy with larger datasets. Even with smaller datasets, anomalies could be detected by comparison with undamaged responses. |

## 3.5 CONCLUSION

The application of three distinct deep learning algorithms: LSTM, Supervised and Unsupervised MTT, and an LSTM-based autoencoder was explored for the purpose of damage detection in a cantilever steel I-beam. Throughout the investigation, various numbers of sampling data points were utilized as input features for these algorithms and it was observed that as the dataset size



### 3.5. CONCLUSION

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increased, particularly in terms of the number of data points used as input features, the performance and reliability of the anomaly detection algorithms improved significantly. Specifically, the algorithms demonstrated accelerated and more accurate training, showcasing heightened proficiency in reconstructing undamaged samples with increased precision and speed. Furthermore, despite employing smaller datasets with fewer data points, the algorithms, notably the Supervised and Unsupervised Multivariate Time series Transformers, exhibited commendable resilience in detecting anomalies within damaged data. This capacity to discern irregularities in damaged sections, while comparing them against undamaged beam responses, highlights the robustness and adaptability of these models even under data-constrained circumstances. Finally, for detecting if an I-beam is damaged or not, based on acceleration time-history response, the three algorithms LSTM, MTT, and LSTM autoencoder showed the best proficiency. Moreover, when localization of damage along the beam was sought, LSTM, Supervised and Unsupervised MTT algorithms showed best accuracy. These outcomes were expected due to the attention mechanism in Transformers, which allows for better focus on relevant parts of the input sequence, and the LSTM's characteristics for capturing sequential temporal data, which enhances their performance in structural health monitoring tasks. Significant progress in structural engineering is possible if AI and ML algorithms can be effectively applied to real-world scenarios. This research focuses on evaluating the adaptability of several ML algorithms for damage detection and localization in I-beams. A broader applicability will be explored in the second phase, targeting artificially induced damage in orthotropic steel decks, bringing LSTM and Multivariate Time-series Transformers closer to practical use with structural health monitoring data from actual bridges. If these ML methodologies demonstrate acceptable accuracy for full-scale structures, they could revolutionize the monitoring of steel bridges and establish new methods for prioritizing maintenance and repairs of aging infrastructure. Overall, this study not only sheds light on the potential of deep learning algorithms in structural health monitoring but also emphasizes their adaptability to different data sizes and their efficacy in damage detection tasks. The insights garnered from this research could potentially contribute to the development of more robust and efficient methodologies for structural health monitoring and anomaly detection in civil engineering applications.

# CHAPTER 4

## INTEGRATED PS-IN SAR AND MACHINE LEARNING FRAMEWORK FOR MONITORING BRIDGE DISPLACEMENT: VALIDATION ON THE VICTORIA BRIDGE IN MONTREAL, CANADA<sup>1</sup>

### 4.1 ABSTRACT

Reliable and continuous monitoring of aging transportation infrastructure such as the Victoria Bridge in Montreal, Canada, is essential for ensuring long-term safety and performance. In this study, the Persistent Scatterer Interferometric Synthetic Aperture Radar (PS-InSAR) technique was applied to analyze structural displacements of the bridge using both ascending and descending Sentinel-1 satellite data. The interferometric processing was conducted using SNAP and StaMPS software. To enhance interpretability, a thermal sensitivity analysis was carried out to examine the relationship between temperature variations and structural movement. To support automated interpretation, a machine learning-based anomaly detection framework was implemented. Temporal and statistical features were extracted from the displacement time series of persistent scatterer points, and the Isolation Forest algorithm was employed to identify abnormal structural behavior. Anomaly scores were assigned, and SHapley Additive exPlanations (SHAP) were used to interpret the contribution of each feature to the anomaly classification. Visualizations, including anomaly heatmaps and displacement plots, provided insight into both spatial and temporal anomalies. The proposed framework demonstrates the potential of combining satellite-based remote sensing with explainable machine learning techniques for enhanced remote structural health monitoring of civil infrastructure.

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<sup>1</sup>This chapter is based on a manuscript submitted for publication: Sadeghian, E., Cusson, D., Dragomirescu, E., Poncos, V., and Inkpen, D. “An Integrated PS-InSAR and Machine Learning Framework for Bridge Displacement Monitoring.” *Journal of Civil Structural Health Monitoring* (submitted Feb. 2026, under review).

## 4.2 INTRODUCTION

### 4.2.1 BACKGROUND

The structural health of transportation infrastructure is a critical concern as many bridges worldwide approach or exceed their intended service life. Early detection of abnormal displacement is essential for timely identification of potential structural faults which thus can be quickly addressed to maintain safety, ensure reliability, and minimize maintenance costs. Traditional monitoring methods, such as visual inspection and point-based sensors, often provide limited spatial coverage and can be resource-intensive, making them less suitable for continuous long-term surveillance of large structures [83]. As a result, satellite-based remote sensing has emerged as a powerful tool for critical civil infrastructure monitoring.

Interferometric Synthetic Aperture Radar (InSAR) has been widely applied to measure ground deformation with millimeter-level accuracy by exploiting the phase difference between successive radar acquisitions [84]. Within this framework, the Persistent Scatterer InSAR (PS-InSAR) technique has proven particularly effective for built environments, where stable natural radar reflectors provide reliable time-series displacement measurements [84–86]. Previous research has demonstrated the successful application of PS-InSAR to monitor infrastructure such as dams, buildings, and transportation networks [9, 87]. Specifically for bridge structures for which the displacement of the deck has an important role in determining its stability, PS-InSAR has provided early warning indicators of structural displacement [88, 89] and been validated against in-situ measurements for Canadian bridges [90]. Internationally, successful applications include monitoring the Brooklyn Bridge in the United States [91], analyzing thermal dilation on the Tsing Ma Bridge in Hong Kong [92], and broader structural monitoring in China [93]. More recently, multi-temporal InSAR (MT-InSAR) has been employed for bridge portfolios and structural interpretation of displacement patterns [40, 94]. These studies collectively illustrate PS-InSAR's promise as a scalable, non-contact method for bridge monitoring across various settings.

## 4.2. INTRODUCTION

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Despite its promise, PS-InSAR faces challenges when applied to bridges. The typically narrow structure can span all or most of a satellite image pixel (e.g., bridge deck width), which may lead to low PS density in the transverse direction, while the underlying water (or road) can cause coherence issues. Additionally, PS points with approximate geolocation coordinates may not be located precisely on the bridge structure, but could represent nearby scatterers, complicating the interpretation of the bridge deck displacement [95]. Thermal expansion and seasonal loading can also dominate displacement signals [96], and atmospheric and geometric distortions can further obscure structural responses. These challenges necessitate refined processing approaches and complementary analyses for reliable remote monitoring of structures. For harsh climates, seasonal temperature variations can induce significant displacements, thus thermal sensitivity analyses are conducted for a better interpretation of the bridge-specific displacement trends [97].

Recent studies have further demonstrated the potential of multi-temporal InSAR for bridge-specific structural assessment and interpretation, highlighting its effectiveness in capturing subtle deformation patterns [40, 94]. Nevertheless, the interpretation of PS-InSAR displacement time series has traditionally relied on manual, labor-intensive analyses, which limit data scalability and can introduce subjectivity when selecting the early warning displacement thresholds. To address this challenge, machine learning techniques have been increasingly adopted for structural anomaly detection in large and complex datasets [44, 98]. Deep learning techniques have also demonstrated their effectiveness in component-level structural damage detection [99]. The present study shifts to infrastructure-scale monitoring by applying the Isolation Forest algorithm to PS-InSAR displacement time series for the Victoria Bridge in Montreal, Canada. This unsupervised ML approach can detect anomalies without labeled training samples [48]. Given the safety-critical nature of bridge displacement evaluation, it is not sufficient to simply label a data point as anomalous; it is equally important to understand why the specific data point has been classified as anomalous. Explainable artificial intelligence methods address this need by linking anomalies to the underlying features that drive the detection outcome. Among these, SHapley Additive exPlanations (SHAP) provides a rigorous framework for quantifying the relative contribution of each feature to the anomaly score, thereby offering transparency into the identification of factors responsible for abnormal structural behavior [53].

## 4.2. INTRODUCTION

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In this study, an integrated framework was developed that leverages PS-InSAR and explainable ML-based anomaly detection to monitor deck displacement of the Victoria Bridge. Sentinel-1 data from both ascending and descending orbits are processed using the Sentinel Application Platform (SNAP) [100] and the Stanford Method for Persistent Scatterers (StaMPS) [101] to generate displacement time series, which are then analyzed with thermal sensitivity evaluation, and machine learning-based anomaly detection explained through SHAP. This approach ties remote sensing insights with transparent and scalable infrastructure monitoring.

### 4.2.2 PRINCIPLES OF InSAR AND PS-InSAR

Interferometric Synthetic Aperture Radar is a radar remote sensing technique used to measure small-scale ground or structural displacements by analyzing the phase difference of co-registered pixels between radar images acquired at different times. Unlike optical imaging, which relies on reflected sunlight, SAR is an active sensor that transmits microwave signals and records their backscattered response. This makes it effective in all weather conditions and during both day and night [102]. Because of these advantages, InSAR has been widely applied in natural hazard monitoring, land subsidence analysis, and more recently, in structural health assessment. [103, 104].

A significant advancement over conventional InSAR is the Persistent Scatterer InSAR technique. Persistent scatterers are radar targets including natural and man-made targets like buildings, bridges, dams, etc. that maintain a stable radar reflection over long periods of time. By focusing on these PS points, PS-InSAR reduces noise caused by vegetation, temporal decorrelation, and atmospheric disturbances, thereby enabling millimeter-scale displacement monitoring over long time series. [9, 84, 105].

**The fundamental equations describing these contributions are provided in section 2.3.1 of this thesis.**

## 4.2. INTRODUCTION

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### 4.2.3 ISOLATION FOREST ALGORITHM

As a general feature, an anomaly detection algorithm aims to identify data points that deviate significantly from the majority of observations. In the context of PS-InSAR applied to bridges, anomalies correspond to displacement patterns that differ from expected long-term structural behavior. The Isolation Forest (iForest) algorithm is a widely used unsupervised ML-based method for anomaly detection in high-dimensional datasets [48], thus it finds good applicability for the current problem. Unlike other approaches that attempt to model normal behavior, iForest relies on the principle that anomalies are both rare and different, and therefore easier to isolate from the rest of the data [49].

The algorithm constructs an ensemble of randomly generated binary trees, referred to as isolation trees (iTrees). At each split, a feature is selected at random and divided at a randomly chosen threshold. Because anomalous points differ substantially from the majority, they are typically isolated after only a few splits, resulting in shorter average path lengths. In contrast, normal points require more splits and thus have longer paths [44].

Based on this algorithm, anomaly score for an observation  $x$  in a dataset of size  $n$  is defined in the original formulation as:

$$s(x, n) = 2^{-\frac{E(h(x))}{c(n)}} \quad (4.1)$$

where  $h(x)$  is the path length of  $x$  in an isolation tree,  $E(h(x))$  is the expected path length across all trees, and  $c(n)$  is the average path length of unsuccessful searches in a Binary Search Tree, approximated by:

$$c(n) = 2H(n-1) - \frac{2(n-1)}{n} \quad (4.2)$$

with  $H(i) \approx \ln(i) + 0.577$  representing the harmonic number.

In this theoretical form, the score ranges between 0 and 1, where values close to 1 suggest strong anomalies, and values near 0 indicate normal points. However, in practical implementations

### 4.3. CASE STUDY AND SAR DATA

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such as scikit-learn [50], the anomaly score is instead provided as a continuous value that can be either positive or negative. In this setting, anomalies are identified by applying a threshold, typically zero, such that scores below the threshold correspond to anomalies, while scores above it correspond to normal observations. This threshold-based approach allows flexibility in adapting the method to specific datasets and monitoring needs.

Because it is unsupervised, efficient and able to handle large datasets, Isolation Forest is well suited for analyzing PS-InSAR displacement features. Its ability to assign an anomaly score to each PS measurement point also facilitates subsequent interpretation using explainability methods.

## 4.3 CASE STUDY AND SAR DATA

The case study focuses on the Victoria Bridge located in Montreal, Canada, a 160-year-old structure that represents a critical component of the Canadian National Railway (CNR) network (Fig. 5.1). The bridge spans 2790m distance across the St. Lawrence River, linking the cities of Montreal and Saint-Lambert. The bridge has a total of 26 simply supported spans, consisting of through trusses, deck trusses, girder spans, and two lift spans that carry two railway tracks and four roadway lanes. The railway tracks are supported by a deck composed largely of timber ties, while the roadway surface consists mainly of steel grating. Roadway lanes are cantilevered from the through trusses and supported by floor beam extensions. Given its age, complex design, and strategic role as a transportation corridor, Victoria Bridge represents an excellent candidate for structural health monitoring using remote sensing methods.

To monitor bridge displacement over time, C-band Synthetic Aperture Radar (SAR) data from the Sentinel-1 satellite mission were employed. Sentinel-1 is part of the European Space Agency's Copernicus Earth Observation Program and provides consistent global radar coverage suitable for Earth surface monitoring [100, 106]. Copernicus mission operates at a wavelength of approximately 5.6 cm, and the Interferometric Wide Swath mode was selected for its suitability to PS-InSAR applications. The IW mode employs the Terrain Observation with Progressive Scans

#### 4.3. CASE STUDY AND SAR DATA

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Figure 4.1: Study area: the Victoria Bridge in Montréal, Canada.

SAR (TOPSAR) technique, which segments the radar swath into three sub-swaths and further into burst segments. This configuration delivers uniform image quality, a swath width of 250 km, and high coherence between repeated acquisitions, making it particularly effective for interferometric SAR applications [107].

Both descending and ascending passes were acquired. In descending mode, the satellite path is oriented from north to south with a west-looking viewing geometry of the bridge, while in ascending mode it travels south to north with an east-looking bridge viewing geometry.

A total of 116 descending and 114 ascending Sentinel-1A scenes covering the Victoria Bridge were collected from January 2020 to December 2024 via the Alaska Satellite Facility (ASF) Data Search Vertex [108] which were used to develop the interferograms for the time-series analysis.

For this study, vertical-vertical (VV) polarization was selected for both ascending and descending passes. VV polarization typically yields stronger and more stable radar returns over metallic and flat structural surfaces compared to cross-polarized channels such as vertical-horizontal (VH). This ensures higher interferometric coherence across repeated acquisitions and improves the reliability of PS-InSAR displacement estimates [9].

By combining ascending and descending datasets acquired in VV polarization, this study maximizes sensitivity to both vertical and horizontal deformation components. This compre-



#### 4.4. DATA PREPROCESSING AND PS-INSAR WORKFLOW

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hensive dataset provides the foundation for subsequent PS-InSAR processing, thermal sensitivity analysis, and anomaly detection.

## 4.4 DATA PREPROCESSING AND PS-INSAR WORKFLOW

Processing Sentinel-1 data for PS-InSAR analysis requires a structured workflow to extract reliable phase information and prepare displacement time series for interpretation. Preprocessing was performed using SNAP2StaMPS, which interfaces SNAP with StaMPS. SNAP handled interferometric preparation, and StaMPS performed persistent-scatterer identification and time-series estimation [85, 100, 101].

Because only a fraction of each Interferometric Wide Swath (IW) acquisition covers the bridge, the workflow began with burst selection using a bounding box enclosing the Victoria Bridge footprint. This spatial subset preserved full azimuth and range resolution over the structure while reducing computational load. Precise orbit files were then applied to all scenes to refine satellite position and velocity, thereby reducing orbital phase ramps and improving co-registration accuracy.

All secondary images were subsequently co-registered to a single master scene (8 August 2022), chosen for its central position in time and favorable perpendicular baseline. The perpendicular baseline in InSAR is the across-track separation between two satellite positions. Co-registration used back-geocoding so that pixels align in geocoded space, ensuring that phase differences are computed for the same ground locations. For Sentinel-1 TOPS (Terrain Observation with Progressive Scans) acquisitions, azimuth phase continuity across bursts is sensitive to sub-pixel misregistration; therefore, TOPSAR co-registration with Enhanced Spectral Diversity (ESD) was employed to estimate and correct residual azimuth shifts at burst overlaps, followed by TOPSAR debursting to merge burst segments into no seamless Single Look Complex (SLC) stacks suitable for interferometry. This sequence ensures continuous phase across burst boundaries and avoids artificial discontinuities along the bridge deck.

#### 4.4. DATA PREPROCESSING AND PS-INSAR WORKFLOW

The topographic phase was removed using the SRTM 1-arcsecond DEM ( $\approx 30m$ ), limiting residual elevation errors mainly to DEM noise and local man-made geometry not resolved at DEM scale. Interferograms were then formed by differencing each secondary image with the master image. For the Victoria Bridge dataset, 108 descending and 99 ascending interferograms were generated, providing dense temporal sampling between January 2020 and December 2024 (Table 4.1). For quality control, interferograms with low average coherence over the bridge region were excluded from further processing to reduce the impact of temporal decorrelation and unwrapping errors. Where appropriate, light phase filtering (Goldstein) was applied to improve phase signal-to-noise while preserving sharp gradients along structural edges.

Table 4.1: Geometric parameters for ascending and descending Sentinel-1 passes over the Victoria Bridge.

| Parameter               | Descending Pass     | Ascending Pass      |
|-------------------------|---------------------|---------------------|
| Data Range              | Jan 2020 - Dec 2024 | Feb 2020 - Dec 2024 |
| Number of Scenes        | 108                 | 99                  |
| Incidence Angle         | 45.6°               | 44.5°               |
| Satellite Track Heading | 194.2°              | 345.8°              |
| Bridge Track Heading    | 64.2°               | 64.2°               |

The interferometric stacks, together with amplitude images, baseline information, and meta-data, were exported via SNAP2StaMPS into the directory structure expected by StaMPS. Coherence maps produced during interferogram formation accompanied the export and were used to guide persistent scatterer selection.

StaMPS is a MATLAB-based software designed to identify radar targets that maintain long-term phase stability, enabling extraction of millimeter-scale displacement time series even in the presence of noise and atmospheric disturbances [85, 101]. Initially, PS candidates were identified using amplitude statistics and phase stability metrics. Candidates were then weeded to remove spatially redundant points while maintaining coverage along the bridge alignment. Phase unwrapping proceeded across space and across time together using the interferogram network, with screening of unwrapping residues and triplet inconsistencies to reduce error propagation. StaMPS then estimated and removed the atmospheric phase screen (APS) via spatial-temporal

#### 4.5. RESULTS AND ANALYSIS

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filtering, and corrected look-angle-dependent terms to mitigate residual geometric contributions. A stable reference area outside the bridge footprint was selected to define the zero-displacement datum, allowing consistent comparison of PS time series across the structure. The outcome consisted of millimeter-scale LOS displacement time series and velocities for each retained PS in both the ascending and descending stacks. The two stacks were processed with identical parameters and kept separate.

This integrated workflow ensured that only PS exhibiting robust long-term phase stability were retained on and near the bridge, yielding high-quality displacement time series suitable for downstream analyses (displacement thermal sensitivity analysis, and anomaly detection).

### 4.5 RESULTS AND ANALYSIS

#### 4.5.1 PS-IN SAR DISPLACEMENT RESULTS

The PS-InSAR outputs obtained from StaMPS were visualized using the StaMPS Visualizer to examine the distribution of persistent scatterers and the corresponding LOS displacement velocities over the Victoria Bridge. Both ascending and descending datasets produced good PS coverage along the bridge, with denser clusters over the main spans and fewer points in areas with less favorable radar reflections, such as near the water surface. Displacement velocity maps for both satellite passes are shown in Fig. 4.2. In each map, a reference point was selected among the most stable persistent scatterers, based on its displacement time series showing almost no movement during the observation period. In both ascending and descending passes, the displacement of each PS is expressed relative to the selected reference. This ensures that the velocity fields highlight relative movements of the bridge rather than being influenced by long-wavelength orbital or atmospheric effects.

To better illustrate the temporal evolution of displacement, typical LOS time series were extracted from selected PS on the bridge deck and near structural supports. These time series, extracted along a period of five years from January 2020 to December 2024, reflect the seasonal

#### 4.5. RESULTS AND ANALYSIS

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temperature fluctuations, which are consistent with thermal expansion and contraction of the bridge materials. While the general displacement patterns from ascending and descending passes are consistent, the amplitudes recorded by the satellite during the two passes differ due to their distinct radar viewing orientation, which are more or less sensitive to vertical or horizontal motion. During initial processing, some interferograms over the bridge area showed low coherence, and a few time series contained sudden peaks. These were linked to phase unwrapping errors and poor-quality interferograms during winters, when the bridge is covered by snow and ice, thus its deck exhibits poor reflection for the radar measurements. After removing low-coherence interferograms and adjusting unwrapping parameters, the number of PS points decreased over the bridge. Although fewer scatterers were retained, the remaining time series became smoother and more reliable (Fig. 4.3). This refinement step is common in PS-InSAR analysis and helps ensure that the final results represent bridge displacements rather than processing potentially unreliable data.

Overall, the PS distribution maps (Fig.4.2) and displacement time series from both ascending and descending satellite passes provide a reliable baseline for further analysis. In the following subsections, these LOS measurements are examined for thermal sensitivity and used as input features for anomaly detection.

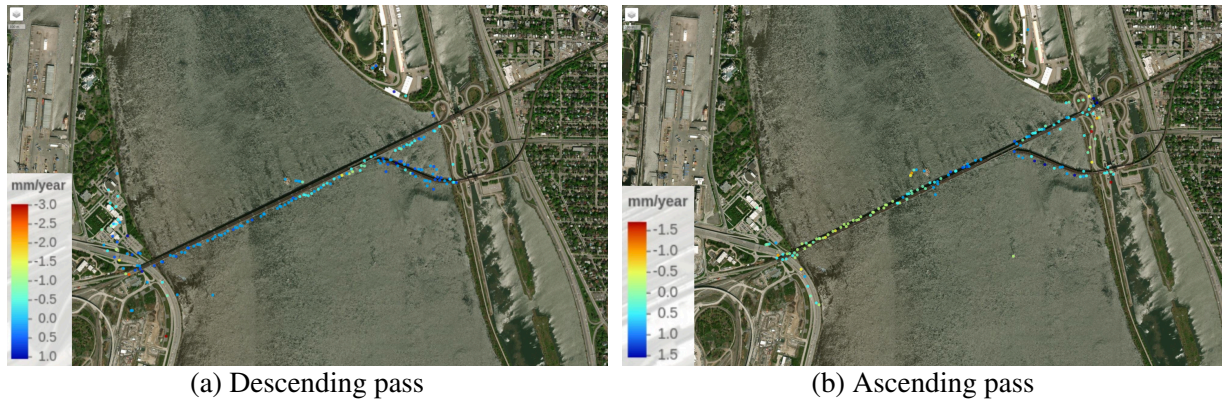


Figure 4.2: Distribution of persistent scatterers (PS) identified over the Victoria Bridge.

## 4.5. RESULTS AND ANALYSIS

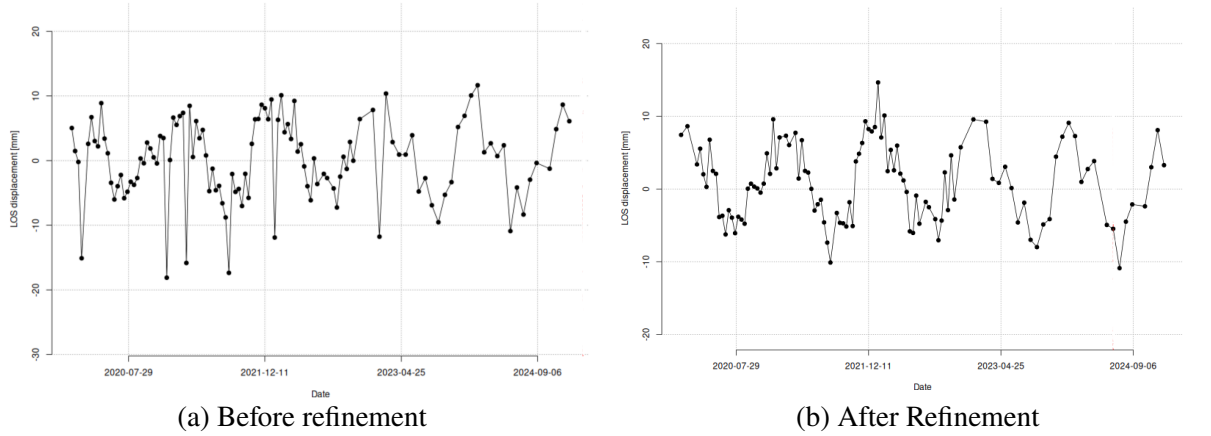


Figure 4.3: Example of displacement time series before and after refinements.

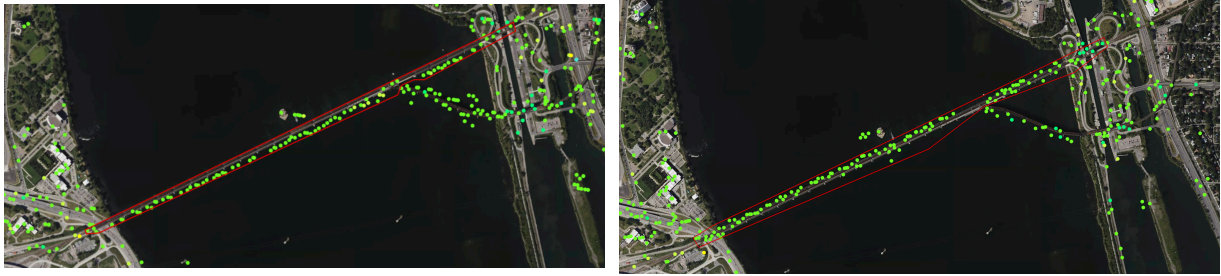
### 4.5.2 BRIDGE THERMAL DISPLACEMENT SENSITIVITY ANALYSIS

The most significant changes in the measured displacement were noticed to occur during the seasonal cycles of the bridge. Therefore the thermal sensitivity of the bridge displacement was investigated for both ascending and descending LOS datasets. To prepare the data, the StaMPS results were first formatted and uploaded to the C-GMS (Canadian Ground Motion Service) platform, where persistent scatterers located only on the bridge deck and trusses were selected and exported (Fig. 4.4). This ensured that subsequent analysis focused exclusively on the structural elements of interest. The Canadian Ground Motion Service is a national InSAR based monitoring platform that provides millimetre-level measurements of ground and infrastructure deformation across Canada. Using Sentinel-1 radar data and PS-InSAR processing, C-GMS generates long-term velocity maps and displacement time series that help identify subsidence, structural movement, and other deformation trends [109].

Before evaluating the thermal response, the LOS displacement of each PS point was detrended to remove long-term deformation components. This step isolates short-term variations that are more directly correlated with temperature, ensuring that regression results capture thermal effects rather than background structural trends.

#### 4.5. RESULTS AND ANALYSIS

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(a) Descending pass

(b) Ascending pass

Figure 4.4: Bridge-only PS selection in C-GMS prior to export.

For each PS point, LOS displacement values were paired with hourly air temperature records from the nearest weather station, selected at times of satellite passes (06:56 EDT for descending and 18:52 EDT for ascending). A simple linear regression was then applied, with displacement as the dependent variable and temperature as the predictor. The slope of the regression represents the thermal sensitivity of each PS point in millimeters per degree Celsius, with positive slopes indicating motion away from the satellite as temperature increases and negative slopes indicating motion toward it.

The overall distribution of thermal sensitivity across PS points is illustrated with histograms for both ascending and descending passes (Fig.4.5). It can be seen that the standard deviation for ascending pass is higher, and the values are more distributed than the descending pass. To visualize the spatial variation of thermal behavior, heatmaps were generated which show the sensitivity to temperature of each PS point along the bridge alignment (Fig.4.6). Finally, to provide an engineering interpretation, the PS points locations were projected onto an axis along the bridge deck layout, allowing thermal sensitivity to be plotted directly against bridge layout (Fig. 4.7). These LOS thermal displacement sensitivity profiles reveal a clear and physically consistent deformation behavior. In the ascending pass, LOS thermal displacement sensitivity

#### 4.5. RESULTS AND ANALYSIS

values are negative from the left end to the midspan, indicating motion toward the satellite, and positive from the midspan to the right end, indicating motion away from the satellite. The descending pass, which observes the bridge from the opposite direction, displays an inverse trend: positive values from the left end to the midspan and negative values from the midspan to the right end. This complementary pattern confirms that PS points on both sides of the bridge are expanding away from the center span in the longitudinal direction of the bridge.

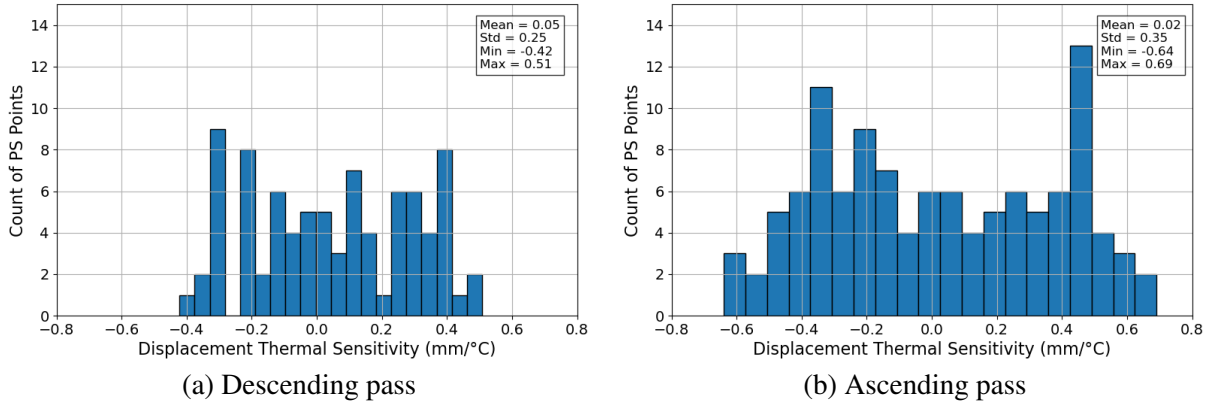


Figure 4.5: Histograms of thermal sensitivity across PS points.

The interpretation of displacement thermal sensitivity is also supported by the structural configuration of the Victoria Bridge. The bridge is composed of 26 simply supported spans, each acting independently with supports only at the ends, rather than transferring bending moments continuously between spans [110]. This structural arrangement means that thermal expansion and contraction are primarily local to each span, reducing the need for complex finite element modeling (FEM) to interpret the observed thermal behavior. Simple hand calculation suffices.

Together, these results provide a comprehensive picture of how the Victoria Bridge responds thermally under different satellite viewing geometries. They also form the basis for subsequent feature extraction and anomaly detection.

#### 4.5. RESULTS AND ANALYSIS

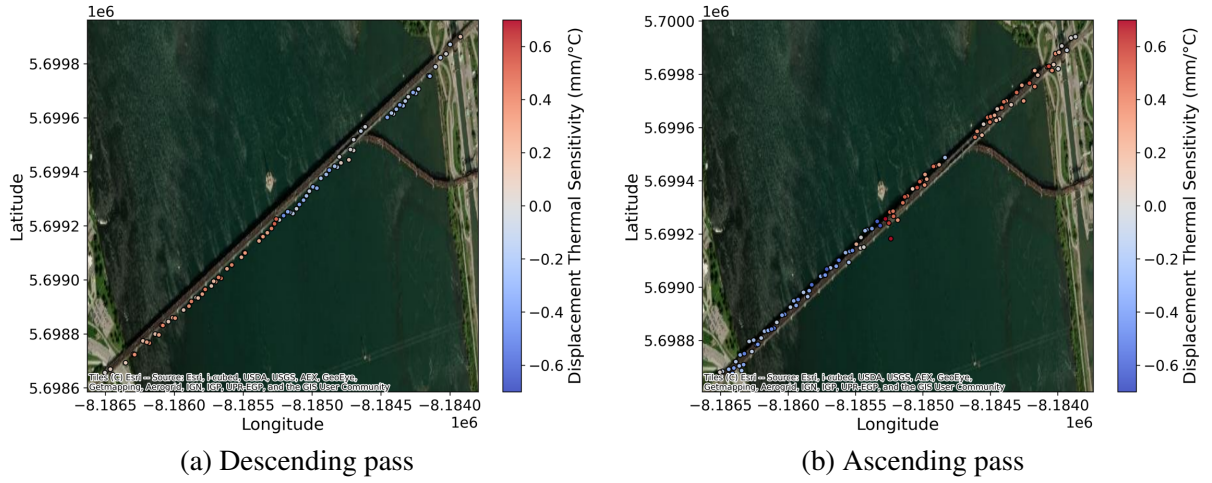


Figure 4.6: Heatmaps of thermal sensitivity values mapped onto PS locations.

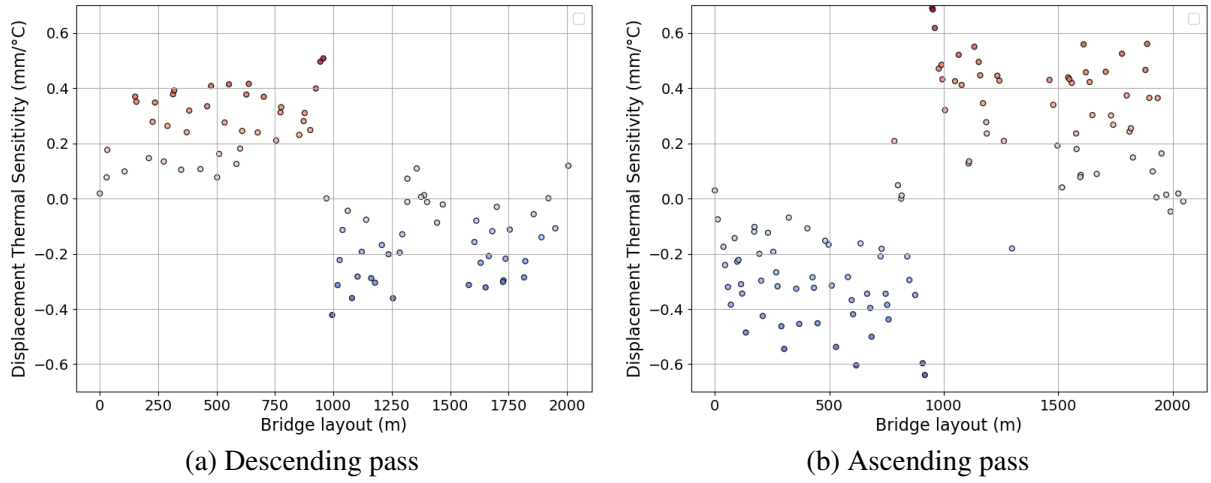


Figure 4.7: Displacement thermal sensitivity plotted against bridge layout.



## 4.5. RESULTS AND ANALYSIS

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### 4.5.3 ANOMALY DETECTION IN BRIDGE DISPLACEMENT DATA

In this part of the study, the focus is on identifying unusual or unexpected patterns in the bridge displacement results. A fully automated workflow was developed in Python to carry out the complete analysis, from feature extraction to anomaly detection and visualization of the LOS displacements of the bridge deck. The PS-InSAR time series from both ascending and descending satellite passes were processed to derive a range of descriptive features, including displacement velocity, thermal sensitivity, seasonal behavior, which formed a set of statistical indicators of data stability. These features were then used as inputs to the Isolation Forest algorithm, a machine-learning method designed to detect scatterers whose behavior deviates from the expected deformation trends. The resulting outputs, presented as anomaly maps, histograms and time-series comparisons, provide a clear overview of the areas on the bridge that exhibit irregular motion or anomalous displacement behavior or a faulty PS measurement.

#### FEATURE EXTRACTION FROM PS-IN SAR TIME SERIES

Employing the entire dataset resulting from the PS-InSAR analysis, the same PS points identified during the thermal sensitivity analysis were considered, restricted to those located directly on the Victoria Bridge. From the displacement time series of these points, a set of 13 statistical and temporal descriptors was derived to capture different aspects of bridge structural behavior. These features, which include: velocity, standard deviation, auto correlation, mean absolute deviation (MAD), maximum jump in displacement time-series data, RMSE, trend and seasonal strength, skewness and kurtosis, quantify not only the long-term displacement rates but also variability, persistence, and sensitivity to environmental effects, such as seasonal temperature variations.

To evaluate redundancy among candidate features, correlation matrices were generated for both the ascending and descending passes (Fig. 4.8). As expected, certain features, such as velocity and displacement slope, exhibited strong positive correlations, reflecting their direct functional relationship. In contrast, features like thermal displacement sensitivity and seasonal strength showed weaker correlations, as they influence one another but are not directly derived or representative of the same underlying parameter. Overall, the correlation patterns were broadly

#### 4.5. RESULTS AND ANALYSIS

similar between the two passes, though the ascending data exhibited slightly stronger relationships among variability-related metrics, likely reflecting its afternoon acquisition time when the bridge experiences more thermal variation, causing stronger interdependence among features linked to short-term changes. Based on these analyses, the redundant features (slope, standard deviation, maximum jump, RMSE) were removed, and a consistent feature set was retained for both viewing geometries (Table 4.2).

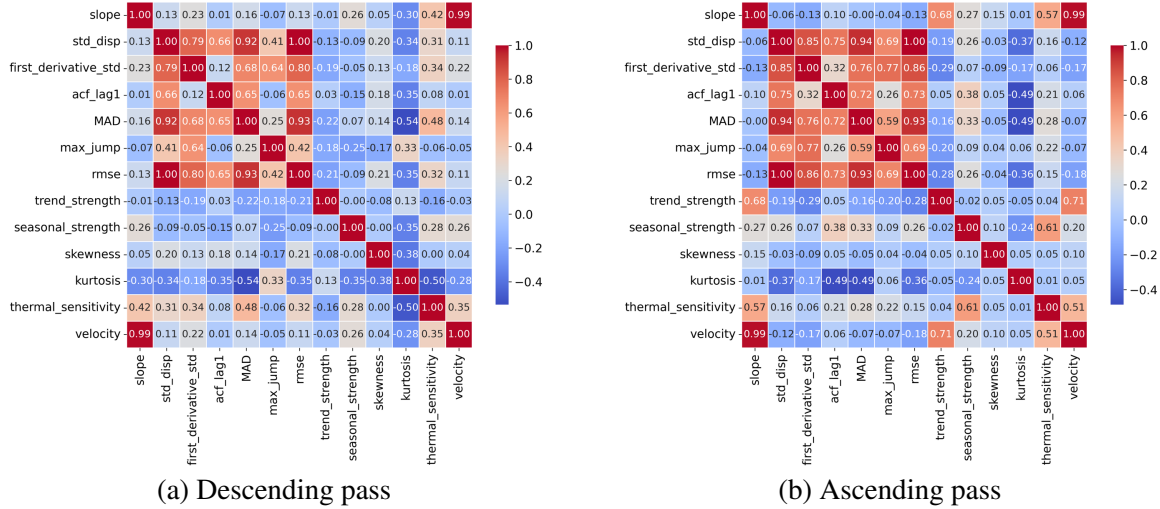


Figure 4.8: Feature correlation matrix.

Together, these nine features provide a comprehensive representation of each PS point's displacement characteristics. The same extraction and filtering procedure was applied to both ascending and descending datasets to ensure that the subsequent Isolation Forest analysis operates on a consistent feature space, enabling direct comparison of results.

#### ISOLATION FOREST ANALYSIS

The selected feature set (Table 4.2) was used as input to an Isolation Forest model to identify PS points with behavior deviating from the typical displacement patterns observed on the bridge. Separate models were trained for the ascending and descending datasets to account for differ-

#### 4.5. RESULTS AND ANALYSIS

Table 4.2: Selected features used for anomaly detection and their interpretation.

| Feature                             | Description and Relevance                                                                                                            |
|-------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------|
| Velocity                            | Long-term displacement rate, representing gradual settlement or deformation trends along the bridge.                                 |
| Median Absolute Deviation (MAD)     | Robust measure of variability that highlights scatter in displacement time series due to noise or local instability.                 |
| First-Difference Standard Deviation | Quantifies short-term fluctuations between consecutive acquisitions, capturing irregular or transient behavior.                      |
| Autocorrelation (Lag 1)             | Indicates temporal persistence; high values suggest stable, predictable movement, while low values reflect random or erratic motion. |
| Trend Strength                      | Degree to which a long-term trend dominates the time series, useful for identifying consistent directional deformation.              |
| Seasonal Strength                   | Reflects the magnitude of cyclic variations due to thermal expansion or recurring loading effects.                                   |
| Displacement Thermal Sensitivity    | Measures the displacement response per °C, linking structural behavior directly to temperature variations.                           |
| Skewness                            | Describes asymmetry in displacement distribution, revealing bias toward uplift or settlement.                                        |
| Kurtosis                            | Measures the presence of extreme values; high kurtosis may indicate intermittent structural anomalies or abrupt displacement events. |

ences in line-of-sight (LOS) geometry, while maintaining identical feature configurations and hyperparameters for both, ensuring direct comparability of results.

The Isolation Forest algorithm isolates anomalies by recursively partitioning the feature space; points that can be separated in fewer partitions are assigned higher anomaly scores. In this study, the model was configured with 300 trees as the number of estimators `n_estimators = 300`, to achieve stable ensemble behavior. Each tree was trained on a random subsample

#### 4.5. RESULTS AND ANALYSIS

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of size `max_samples = 256`, enabling the model to generalize while preserving computational efficiency. The parameter `max_features = 1.0` ensured that all input features contributed to the decision process at each split, preventing bias toward specific attributes. The expected proportion of anomalies was determined automatically using `contamination = 'auto'`, allowing the algorithm to infer the fraction of outliers based on data distribution. Finally, a fixed random seed (`random_state = 42`) was applied to ensure reproducibility across the runs. These settings were selected to balance robustness, computational performance, and consistency between ascending and descending analyses.

##### ISOLATION FOREST ANALYSIS - GLOBAL ANOMALY BEHAVIOR

The Isolation Forest model assigns an anomaly score to each PS point, reflecting how strongly its displacement behavior deviates from the general bridge trend. These scores are automatically normalized, such that the decision threshold for anomaly detection occurs at zero, providing a consistent baseline for both ascending and descending satellite passes. The anomaly score distributions for the two passes (Fig.4.9) shows that most PS points cluster above zero, confirming that the majority of scatterers exhibit stable and consistent deformation behavior. A smaller number of points fall below the zero threshold, representing the points with displacement characteristics that deviate from the dominant pattern. In Figure 4.9 it can be noticed that the descending pass displays a slightly broader score distribution, suggesting greater variability in the west-looking satellite orientation due to subtle differences in radar backscatter and atmospheric path delay. In contrast, the ascending pass exhibits a narrower anomaly score distribution, but higher sensitivity to short-term fluctuations, a pattern reflected later in the higher importance of the first-difference standard deviation feature. Together, these results indicate that the two viewing satellite orientations respond differently to deformation dynamics in the case of the Victoria Bridge: the ascending pass is more responsive to rapid local variations, while the descending pass captures longer-term stability and broader displacement gradients.

This difference in score dispersion (Fig.4.9) also helps explain why the first-difference standard deviation feature plays a stronger role in the ascending pass but not in the descending one.

#### 4.5. RESULTS AND ANALYSIS

Because the descending pass already exhibits a wider natural spread of anomaly scores, short-term fluctuations contribute less additional discriminative power, these variations are effectively “absorbed” within the broader distribution. In contrast, the ascending pass, characterized by lower baseline variability, highlights even small inter-acquisition displacement changes, making the first-difference standard deviation a more decisive indicator of abnormal motion. This complementary relationship between anomaly-score distribution and feature sensitivity underlines the physical consistency of the model’s behavior across the two viewing satellite orientations.

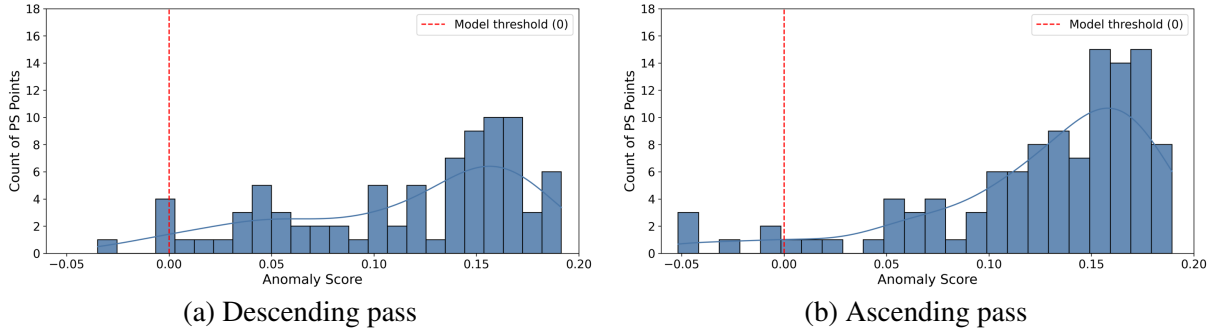


Figure 4.9: Anomaly score distributions.

To assess if these anomalies are detected consistently, a stability analysis was performed by repeatedly bootstrapping the Isolation Forest model. The stability computation was performed via 30 bootstrap runs (`n_runs = 30`, `sample_frac = 0.8`), yielding stable points when the stability score is around 0 and labeling points as anomalous only when their stability score exceeded 0.7. The resulting stability histograms (Fig.4.10) represent the proportion of model runs in which each PS point was classified as anomalous. In Figure 4.10 the maximum value on the vertical axis for each pass is set to the total number of PS points in that pass. Most PS points exhibit stability values below 0.3, indicating that they were rarely flagged as outliers across multiple runs. However, a smaller subset of points shows stability scores above 0.7, identifying them as persistent anomalies that remain detected consistently, despite random resampling within the runs. These high-stability PS anomalies are the most reliable indicators of atypical structural or environmental bridge behavior at these points and form the basis for subsequent spatial and engineering interpretations.

#### 4.5. RESULTS AND ANALYSIS

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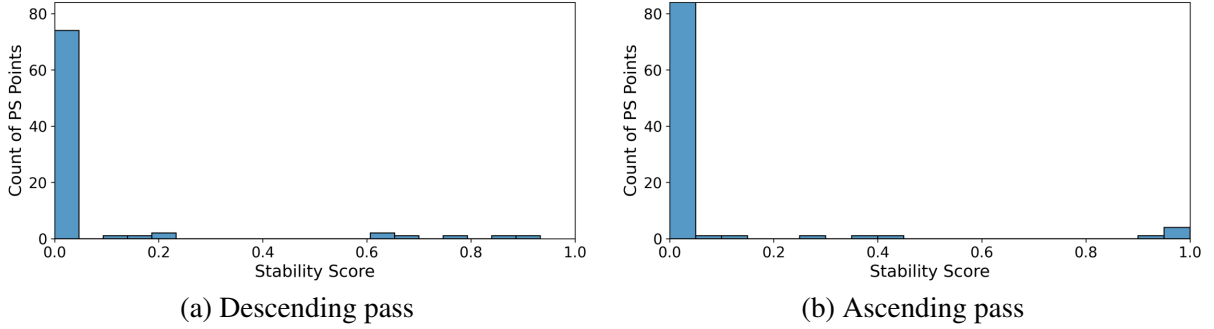


Figure 4.10: Stability of anomaly detection.

Feature importance plots (Fig. 4.11) confirm that the Isolation Forest relies primarily on a compact set of features to identify anomalous behavior. In both passes, trend strength, velocity, kurtosis, and skewness emerge as dominant contributors, indicating that long-term drift, the shape of displacement distributions, and persistent deformation patterns are central to anomaly classification. The first-difference standard deviation remains particularly influential in the ascending pass, consistent with its narrower anomaly-score distribution and greater sensitivity to rapid displacement changes, whereas the descending pass, governed by smoother and more stable dynamics, depends more heavily on trend-related features. These differences in feature ranking correspond closely to the environmental and geometric conditions at satellite acquisition time: the ascending overpass occurs in the afternoon (~7 p.m.), when the bridge experiences cooling down after the mid-day peak solar heating and stronger temperature gradients between shaded and sunlit surfaces. This enhanced diurnal variability amplifies short-term displacement fluctuations, making the first-difference standard deviation a more effective discriminator of anomalies. In contrast, the descending pass takes place in the early morning (~7 a.m.), when the structure is near thermal equilibrium with ambient temperature and atmospheric conditions are calmer, resulting in more stable deformation patterns where long-term drift, captured by *trend strength*, dominates anomaly detection. Additionally, afternoon radar acquisitions are subject to greater tropospheric variability due to convective activity, increasing inter-acquisition noise that further elevates the influence of short-term variability metrics. Differences in ascending and descending line-of-sight (LOS) geometries also contribute: the east-looking ascending configuration emphasizes verti-

#### 4.5. RESULTS AND ANALYSIS

cal and transverse displacements, which can vary rapidly with temperature. Minor differences in coherence and interferogram quality between satellite passes may also influence how much short-term variability contributes to separating typical from atypical deformation behavior.

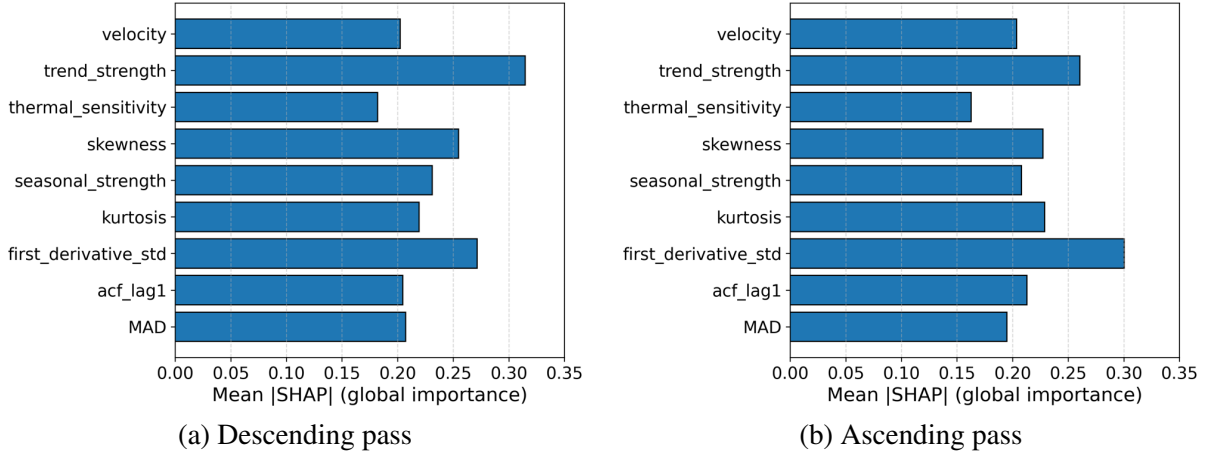


Figure 4.11: Global feature importance based on mean absolute SHAP values.

Class wise SHAP comparisons (Fig. 4.12) provide further interpretability by distinguishing the features that drive normal versus anomalous classifications. For both satellite passes, trend strength exhibits strong influence on identifying the anomalous points, consistent with outliers showing atypical long-term drift relative to their surroundings. In the ascending pass, the elevated importance of first-difference standard deviation and kurtosis reinforces that short-term displacement fluctuations play a larger role in identifying irregular motion under afternoon thermal and atmospheric variability conditions. In contrast, the descending pass, acquired during early morning thermal equilibrium, shows a clearer dependence on long-term drift indicators such as trend strength and velocity. Together, these findings confirm that the model’s decisions align well with the physical conditions at the time of acquisition, enhancing confidence in the anomaly detection results.

#### ISOLATION FOREST ANALYSIS - SPATIAL DISTRIBUTION AND HEATMAPS

The spatial distribution of anomalies provides crucial insight into how detected outliers relate to

#### 4.5. RESULTS AND ANALYSIS

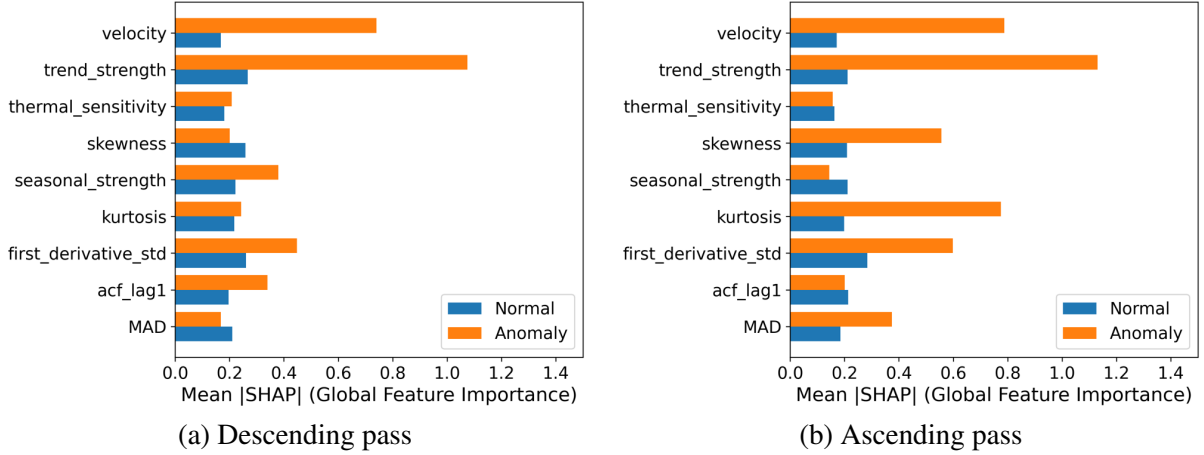


Figure 4.12: Classwise SHAP feature importance, comparing normal and anomalous PS points based on mean absolute SHAP values.

the bridge’s physical structure and loading environment. Figure 4.13 shows the location of the anomalous PS points (highlighted by a yellow circle) identified by the Isolation Forest for both ascending and descending passes. These maps highlight scatterers with anomaly scores below zero (`anomaly_label = -1`), revealing spatial patterns that correspond to local irregularities in deformation behavior. In both passes, anomalous PS points are distributed primarily along the midspan and near the expansion joints at the end of the bridge deck, zones where traffic loads and temperature-induced movement are expected to produce the largest displacement variability, respectively. The similarity in anomaly clusters across both satellite viewing geometries reinforces the physical validity of the detections.

Figure 4.14 illustrates the subset of anomalies that remain consistent across repeated bootstrap models employing 30 runs. Only PS points with stability scores above 0.7 and consensus labels of `-1` are displayed, representing persistent anomalies that were repeatedly detected under different sampling conditions. As the PS anomaly points are identified repeatedly near the end of the deck, it shows that a higher localized mechanical or thermal responses was measured at this location, potentially linked to bearing conditions, deck expansion, or differences in material stiffness. Moreover, their recurrence across both satellite passes, which were determined independently,



#### 4.5. RESULTS AND ANALYSIS

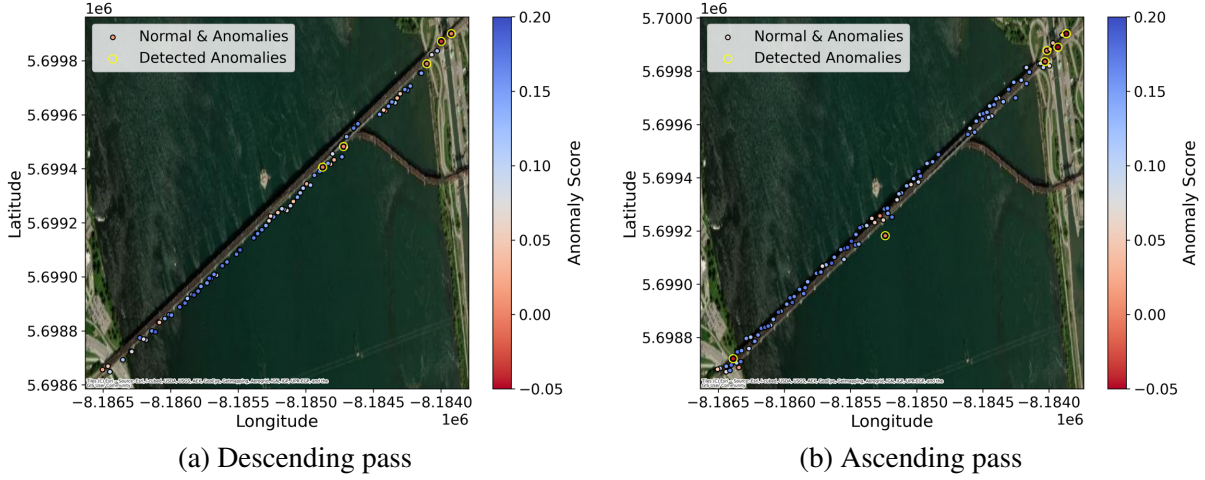


Figure 4.13: Spatial distribution of anomalous PS points from the Isolation Forest.

supports the interpretation that the PS anomaly points represent genuine structural responses rather than atmospheric or data processing noise.

To explore how these detected anomalies relate to measurable displacement quantities, velocity maps were generated for both passes (Fig. 4.15), as the change of displacements with time, over the length of the entire period of five years. These plots visualize the estimated linear displacement rate for each PS point, revealing gradual deformation gradients along the bridge deck. By design, the same framework can be used to visualize any extracted feature, such as thermal sensitivity, seasonal strength, or trend amplitude by mapping their values to the bridge geometry. Thus the proposed framework can be used as a tool which enables targeted inspections of feature-specific behaviors and their correspondence with the identified anomalies.

In addition to feature-value maps, the framework supports visualization of feature-specific anomaly scores. Figure 4.16 presents an example of the velocity feature score, illustrating which areas exhibit the highest contribution to the overall anomaly classification. Regions showing both high feature anomaly scores and high stability can be prioritized for closer engineering review, as they represent areas where the observed deformation behavior is both statistically significant and physically repeatable.

#### 4.5. RESULTS AND ANALYSIS

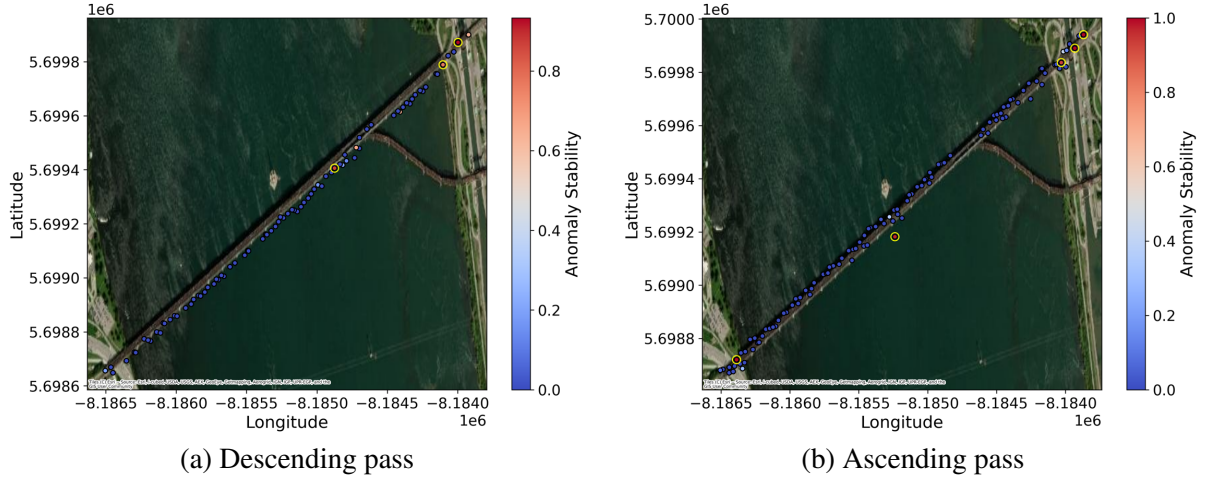


Figure 4.14: Persistent anomalies based on bootstrap stability.

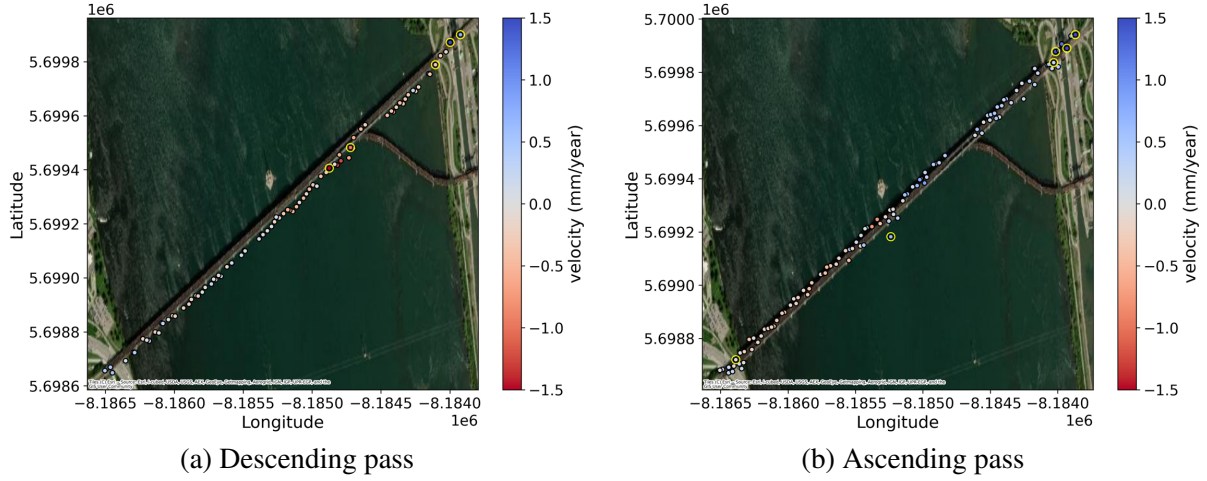


Figure 4.15: Feature value heatmap for linear displacement rate (velocity) at each PS point.

#### 4.5. RESULTS AND ANALYSIS

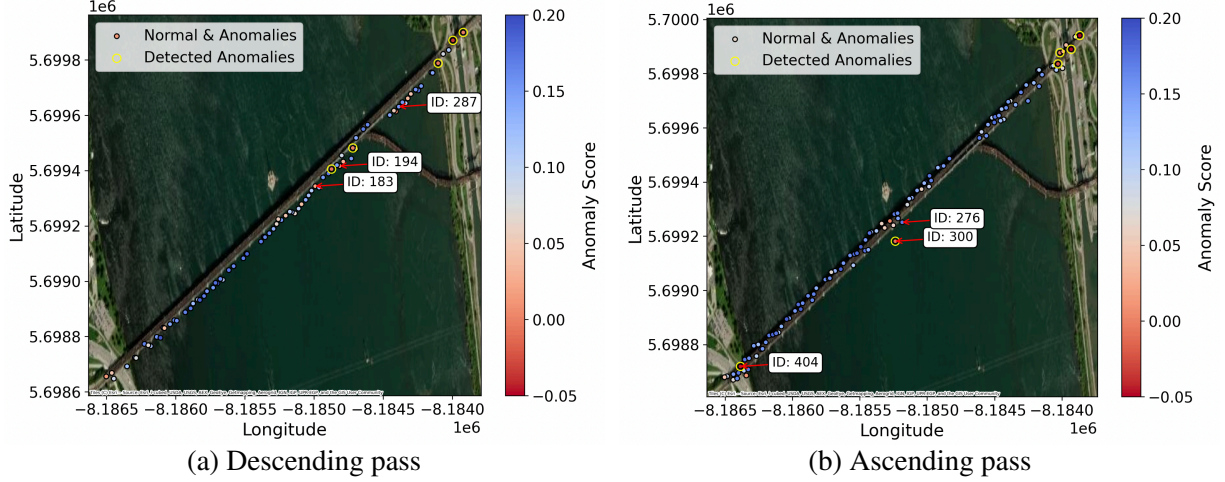


Figure 4.16: Feature anomaly score heatmap for velocity at each PS point.

This visualization tool complementing the proposed framework was implemented entirely in Python, allowing automated generation of heatmaps for any feature value or score in the dataset. Thus the framework provides a remote monitoring solution by integrating PS-InSAR results with data-driven anomaly detection, supporting both visual inspection and quantitative evaluation of bridge displacement behavior.

#### ISOLATION FOREST ANALYSIS - SHAP AND DISPLACEMENT

To better understand why specific PS points were classified as normal and others as anomalous, local explanations were generated by combining SHAP feature attributions with their corresponding displacement time series. Certain PS representative points were selected along the bridge and in Figures 4.17 to 4.22, pairs of plots with complementary insights were provided: the left panels quantifies the contribution of each feature to the anomaly score, while the right panels shows the actual deformation history of the same point. This allows direct interpretation of how different motion characteristics, such as variability, distributional asymmetry, or long-term drift contribute to each classification outcome.

#### 4.5. RESULTS AND ANALYSIS

In the ascending pass, several PS points illustrate the influence of short-term variability and distributional irregularities under afternoon acquisition conditions. For example, PS 300 (Figs. 4.16b and 4.17) was classified as anomalous primarily due to strong negative SHAP contributions from the first-difference standard deviation and median absolute deviation (MAD), consistent with the highly scattered and spiky displacement pattern noticed in its time series. This behavior reflects the higher temporal instability expected during the 7 p.m. overpass, when rapid temperature fluctuations amplify inter-acquisition variability. Another anomaly point for the ascending pass, PS 404 (Figs. 4.16b and 4.18), shows dominant SHAP effects from kurtosis and skewness, indicating a displacement distribution characterized by rare but large excursions and slight bias. Such intermittent outliers likely reflect localized mechanical or thermal responses near structural discontinuities.

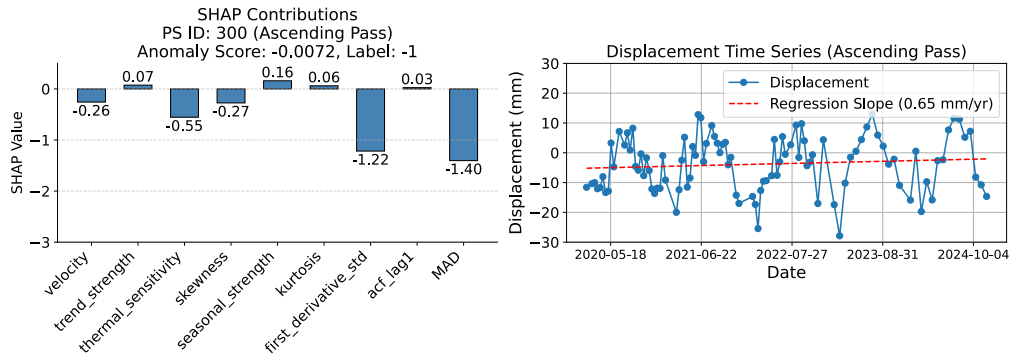


Figure 4.17: Anomalous PS 300 dominated by first-difference standard deviation and MAD, showing abrupt short-term fluctuations.

A contrasting example is PS 276 (Figs. 4.16b and 4.19), a representative normal point in the ascending pass. Its SHAP profile is balanced, with no single feature exerting strong influence and its displacement series remains near zero with minor oscillations, which represents a typical stable and repeatable displacement. Together, these examples confirm that the framework model works for identifying points exhibiting erratic short-term fluctuations or isolated large excursions, while correctly retaining stable scatterers as normal points.

#### 4.5. RESULTS AND ANALYSIS

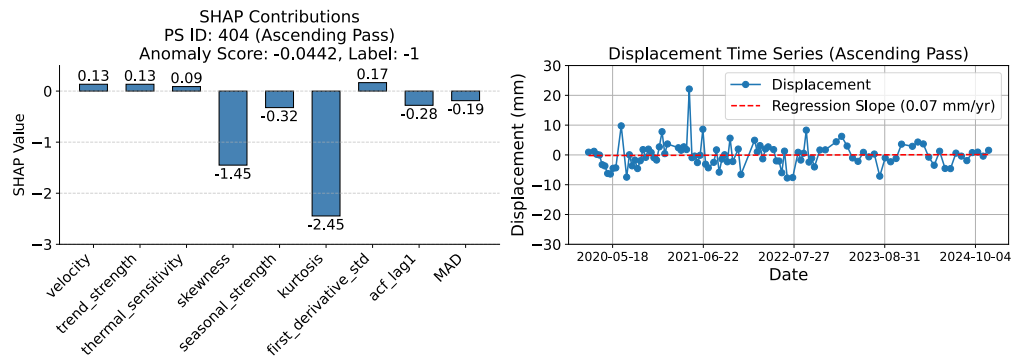


Figure 4.18: Anomalous PS 404 influenced by kurtosis and skewness, reflecting intermittent large displacements.

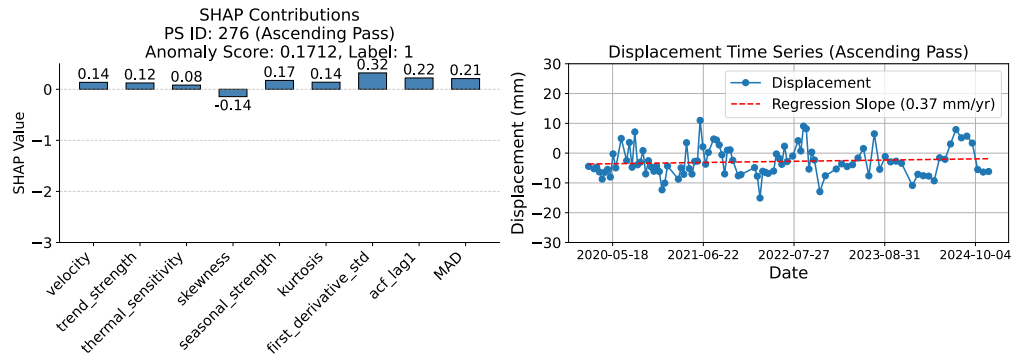


Figure 4.19: Normal PS 276 with balanced feature contributions and stable displacement trend.

## 4.6. DISCUSSION

For the descending pass, acquired in the early morning when the bridge is thermally equilibrated (i.e., close to ambient temperature and with small temperature gradients), the anomaly behavior shifts toward long-term drift and shape-related characteristics. PS 183 (Figs. 4.16a and 4.20) exemplifies a marginally anomalous point dominated by skewness and kurtosis of the displacement data distribution, suggesting persistent asymmetry and occasional abrupt displacements. Its displacement time series indeed shows intermittent bursts superimposed on an otherwise mild trend, consistent with the model's interpretation. PS 194 (Figs. 4.16a and 4.21), despite showing a visible gradual deformation trend, was classified as borderline normal point. In this case, high SHAP values for trend strength and velocity indicate that these features largely explain its motion as a typical long-term drift pattern rather than a true anomaly. Another control case, PS 287 (Figs. 4.16a and 4.22), displays low and diffuse SHAP contributions and a smooth displacement history, further validating the model's ability to distinguish between genuine irregularities and ordinary deformation.

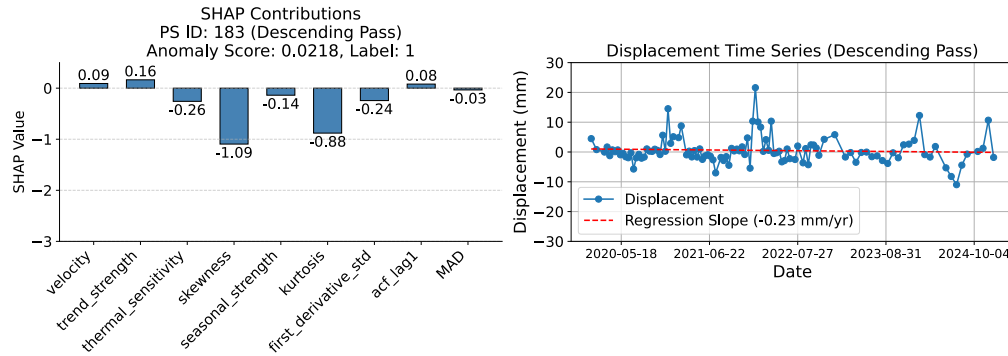


Figure 4.20: PS 183 driven by skewness and kurtosis, showing asymmetric and burst-like motion.

## 4.6 DISCUSSION

Together, the local SHAP explanations and feature-based anomaly detection provide a clear connection between statistical outliers and the physical behavior of the bridge. The ascending pass is

## 4.6. DISCUSSION

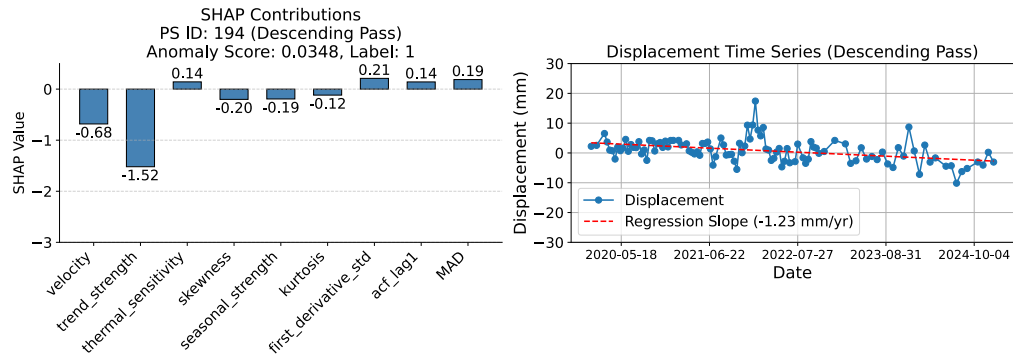


Figure 4.21: Normal PS 194 dominated by trend strength and velocity, reflecting gradual, typical drift.

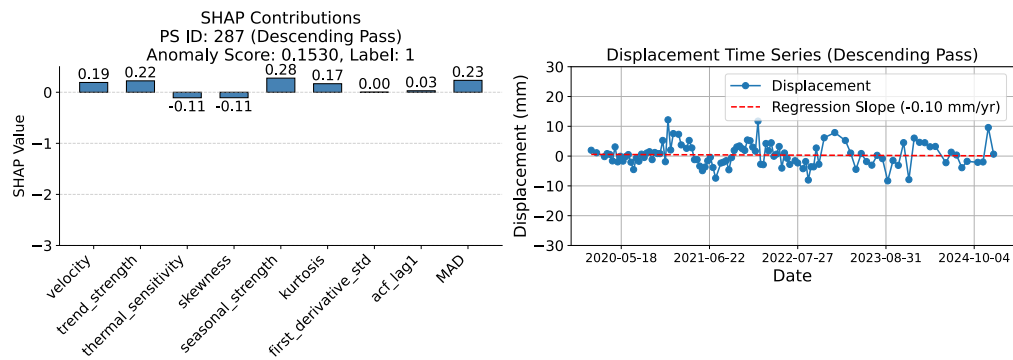


Figure 4.22: Stable PS 287 with low feature impact and smooth displacement history.

#### 4.7. *CONCLUSION*

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more responsive to short-term and distributional irregularities caused by afternoon thermal and atmospheric variability, whereas the descending pass highlights steady, long-term deformation patterns observed under calm morning conditions. The strong agreement between SHAP-derived insights and observed displacement trends shows that the Isolation Forest model captures meaningful, physically grounded signals rather than random correlations. By integrating PS-InSAR time series with explainable machine learning, the framework offers a unified understanding of both local and global deformation mechanisms. The combined analysis from ascending and descending passes delivers a comprehensive view of the bridge's response, capturing rapid, temperature-driven changes as well as gradual, persistent movements. Overall, this automated framework links data-driven anomaly detection with engineering interpretation, establishing a foundation for reliable, long-term remote monitoring of bridges using radar satellite data.

It is also important to emphasize that the detected anomalies represent statistical deviations, not indicators of structural danger. Their magnitudes remain small and are consistent with normal thermal and environmental behavior for a steel bridge. These findings should therefore be viewed as detailed patterns in the displacement data rather than signs of any safety concern for the bridge.

### 4.7 CONCLUSION

The current study focused on developing an integrated framework combining PS-InSAR analysis with explainable machine learning for remote monitoring bridge displacement behavior, using satellite radar data. The integrated framework was demonstrated through an application on the Victoria Bridge in Montreal, for which Sentinel-1 data was collected for the last five years, connecting the physical interpretation of deck displacement with statistically grounded anomaly detection, thus offering a transparent and automated pathway from data preprocessing to engineering insight.

The PS-InSAR analysis of both ascending and descending Sentinel-1 datasets revealed consistent deformation trends primarily governed by temperature variations. The bridge's thermal sensitivity analysis given the simply supported span configuration confirmed that each section



#### 4.7. CONCLUSION

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behaves as expected, where thermal expansion and contraction dominate the displacement response. These findings provided a solid foundation for feature-based modeling, ensuring that the subsequent anomaly detection process was grounded in the underlying physical behavior of the bridge.

A set of statistical and temporal features, including velocity, trend strength, first-difference standard deviation, and thermal sensitivity was extracted from the PS time series to characterize both long-term and short-term displacements time series. The Isolation Forest algorithm, coupled with bootstrap stability analysis, successfully identified PS points exhibiting persistent irregularities while filtering out noise-driven fluctuations. This fully automated Python-based implementation ensures consistent and reproducible anomaly detection, adaptable to other structures or datasets.

Explainable AI tools, specifically SHAP analysis, offered both global and local interpretability of the model decisions. The results revealed that, for Victoria Bridge, the satellite's ascending pass viewing geometry is more responsive to short-term fluctuations driven by afternoon thermal and atmospheric variability, while the descending pass viewing geometry emphasizes gradual deformation trends observed under morning equilibrium. Spatial visualizations of anomaly scores, stability values, and feature-specific heatmaps further reinforced the engineering relevance of the findings, pinpointing regions such as the midspan and expansion joints where displacement variability is naturally expected.

Overall, this work demonstrates that integrating PS-InSAR observations with explainable machine learning provides a scalable and interpretable solution for satellite-based structural health monitoring. By linking feature-driven anomaly detection to real physical mechanisms, the framework connects the gap between data analytics and engineering understanding. Moreover, this approach lays the groundwork for continuous, automated monitoring of critical infrastructure, beyond the practical application exemplified for the Victoria Bridge, Montreal, enhancing the specialists' ability to detect early signs of structural or environmental changes with precision and confidence.

# CHAPTER 5

## A SPATIALLY STRUCTURED AND INTERPRETABLE FRAMEWORK FOR PS-IN SAR ANOMALY DETECTION IN BRIDGE MONITORING<sup>1</sup>

### 5.1 ABSTRACT

Persistent Scatterer Interferometric Synthetic Aperture Radar (PS-InSAR) enables long-term monitoring of bridge displacement; however, interpreting and identifying inconsistencies in the bridge displacement monitoring results remain challenging, due to irregular spatial sampling and variability across satellite datasets. The current study developed a spatially structured and interpretable framework for analyzing PS-InSAR-based anomaly detection by integrating feature-based representation, Isolation Forest, SHAP-based interpretation and spatial filtering along the bridge-axis pre-defined zones. A relative anomaly density metric is introduced to enable comparison across datasets with varying persistent scatterer distributions, and cross-satellite consistency is evaluated using Top-K overlap and Spearman rank correlation. The framework is applied to multi-satellite observations (Sentinel-1, RADARSAT-2 and RCM) over the Victoria Bridge in Montreal. The results show that spatial filtering improves the interpretability of anomaly detection by emphasizing coherent clusters rather than isolated detections. The bridge-deck zone-based analysis reveals that the detected anomalies are not uniformly distributed, but instead concentrate in specific regions along the bridge. While multiple datasets consistently identify a subset of anomaly-prone zones, agreement across satellites remains limited at the level of detailed ranking. These findings indicate that multi-satellite PS-InSAR analysis is more reliable for identifying recurring spatial patterns than for establishing exact agreement in data anomaly intensity. Overall, the proposed framework provides a structured basis for interpreting anomaly patterns, while preserving satellite-dependent variability, supporting more informed use of PS-InSAR for bridge monitoring.

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<sup>1</sup>This chapter is based on publication to be submitted to Journal of Structural Control and Health Monitoring.

## 5.2 INTRODUCTION

Bridges are critical components of transportation infrastructure and are continuously subjected to environmental and operational loads that influence their structural performance over time. Critical infrastructure assets, such as bridges, are progressively aging under increasing traffic demands and harsh seasonal environmental conditions, making continuous structural health monitoring essential for ensuring their long-term safety and performance. Conventional structural health monitoring (SHM) techniques, including visual inspections and in-situ sensing systems, provide valuable information but are often limited in spatial coverage, scalability and long-term continuity [1, 111, 112].

Satellite-based remote sensing, particularly Interferometric Synthetic Aperture Radar (InSAR), has emerged as an effective alternative for large-scale deformation monitoring. Persistent Scatterer InSAR (PS-InSAR) enables the measurement of displacement time series with millimeter-level accuracy over extended periods, independent of weather conditions and daylight [9, 84, 103]. Its capability to monitor infrastructure has been widely demonstrated in both natural and built environments [85, 102, 113]. In the context of bridge monitoring, PS-InSAR has been successfully used to capture long-term deformation patterns and temperature-induced structural responses, highlighting its potential as a complementary tool to conventional SHM systems [88, 90, 114].

The increasing availability of PS-InSAR data has motivated the use of machine learning techniques to analyze displacement time series and identify anomalous structural behavior. In particular, unsupervised anomaly detection methods, such as Isolation Forest, enable the identification of persistent scatterers whose temporal response deviates from dominant patterns without requiring labeled data [48]. These approaches have been increasingly explored in structural health monitoring applications to detect unusual structural responses and potential early-warning signals [43, 99, 115]. In addition, explainable artificial intelligence techniques, such as SHapley Additive exPlanations (SHAP), have been introduced to improve interpretability by quantifying the contribution of individual features to anomaly detection results [53].

## 5.2. INTRODUCTION

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Despite these advances, several challenges remain in the interpretation of PS-InSAR-based anomaly detection results. First, most existing anomaly detection approaches rely on point-wise analysis, where each persistent scatterer is evaluated independently. This limits the ability to interpret anomalies in a structural context, as isolated detections may not reflect meaningful structural behavior. Second, the spatial distribution of persistent scatterers is often irregular and influenced by surface characteristics, particularly in bridge environments surrounded by water or low-coherence areas [9]. This uneven sampling complicates the identification of consistent spatial patterns along the structure.

A further challenge arises from the use of multiple satellite missions. Different satellites, such as Sentinel-1, RADARSAT-2 and RADARSAT Constellation Mission, differ in spatial resolution, revisit frequency, incidence angle and acquisition geometry [9, 116]. These differences result in variations in persistent scatterer density and displacement sensitivity, leading to inconsistencies in anomaly detection results across different datasets. Although multi-satellite InSAR analyses have been explored in geophysical and infrastructure monitoring contexts [116, 117], limited attention has been given to the consistency of anomaly detection outcomes and their interpretation across satellites in bridge monitoring applications.

To address these limitations, this study developed a spatially structured and cross-satellite consistent framework for interpreting PS-InSAR-based anomaly detection results in bridge monitoring. This approach introduces a bridge-axis representation in which persistent scatterers are projected onto the longitudinal axis of the bridge and are aggregated into span-scale pre-defined zones, enabling easier monitored data interpretation at the structural level. The spatial filtering and labeling strategy are developed to enhance the robustness of anomalous data detection by incorporating neighborhood consistency, thereby reducing the influence of isolated or noise-driven detections. Furthermore, a normalized zone-based representation of anomaly distribution is defined to enable comparison across datasets with different persistent scatterer densities. Based on this representation, cross-satellite agreement metrics, including zone ranking and Top-K agreement analysis, are introduced to quantify the consistency of the anomaly patterns identified across multiple satellite missions.

### 5.3. *STUDY AREA AND DATA*

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The proposed framework is applied to a multi-satellite dataset consisting of Sentinel-1, RADARSAT-2 and RADARSAT Constellation Mission observations over the Victoria Bridge in Montreal, considering both ascending and descending acquisition geometries and multiple time periods. This dataset enables a comprehensive evaluation of anomaly consistency across satellites and observation conditions.

The main contribution of this study is the development of a spatially consistent and cross-satellite validated approach for interpreting anomaly detection results derived from PS-InSAR data. By integrating temporal analysis, spatial organization and multi-satellite comparison, the proposed method provides a more reliable and physically meaningful basis for bridge monitoring.

## 5.3 STUDY AREA AND DATA

### 5.3.1 STUDY AREA

The proposed framework is demonstrated on the Victoria Bridge, located in Montreal, which spans the St. Lawrence River and connects the cities of Montreal and Saint-Lambert (Figure 5.1). As one of the oldest and most strategically important bridges in Canada, it serves both railway and roadway transportation and plays a critical role in regional connectivity.

The bridge has an overall length of approximately 1.9 km and consists of 26 simply supported spans forming the main deck, including through trusses, deck trusses, girder sections and lift spans. The structural system supports two railway tracks and multiple roadway lanes, with a combination of steel structural elements and deck components. Due to its age, structural complexity and continuous exposure to environmental and operational loads, the bridge represents a suitable case study for long-term deformation monitoring and structural assessment.

From a remote sensing perspective, the geometry and surrounding environment of the bridge present several challenges. The bridge deck structure is narrow and slender, and it is primarily surrounded by water, which often results in low coherence in SAR imagery. Consequently, persistent

### 5.3. STUDY AREA AND DATA

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Figure 5.1: Study area: the Victoria Bridge in Montréal, Canada [88].

scatterers are typically concentrated on structural elements such as trusses and deck components, leading to an uneven spatial distribution of PS measurement points. These characteristics make the interpretation of PS-InSAR displacement measurement results more complex and highlight the need for spatially structured analysis approaches.

#### 5.3.2 MULTI-SATELLITE DATASET

The three satellite missions exhibit notable differences in spatial resolution, temporal sampling and acquisition geometry, which directly influence the characteristics of the derived PS-InSAR datasets. These differences are reflected in both the number of available scenes and the density of persistent scatterers over the bridge. As shown in Table 5.1, Sentinel-1 provides a relatively large number of observations with moderate spatial resolution, resulting in stable but comparatively sparse PS distributions. In contrast, RCM and RADARSAT-2 offer higher spatial resolution, leading to significantly denser PS coverage, although with varying numbers of acquisitions

### 5.3. STUDY AREA AND DATA

depending on the satellite mission and acquisition time period. In practical terms, Sentinel-1 provides broader and more frequent coverage with lower spatial resolution, whereas RADARSAT-2 and RCM provide denser and more localized bridge measurements due to their higher spatial resolution, with RCM additionally benefiting from a more modern constellation-based acquisition strategy.

Table 5.1: Summary of multi-satellite datasets used for the Victoria Bridge analysis.

| <b>Satellite Dataset</b> | <b>No. Scenes (Asc/Desc)</b> | <b>No. PS Points (Asc/Desc)</b> | <b>Resolution (range × azimuth)</b> | <b>Incidence Angle (Asc/Desc)</b> | <b>Satellite Heading (Asc/Desc)</b> |
|--------------------------|------------------------------|---------------------------------|-------------------------------------|-----------------------------------|-------------------------------------|
| S1 (2016–2018)           | 61 / 37                      | 1,741 / 797                     | 5 × 20 m                            | 44.5°/45.6°                       | 345.8°/194.2°                       |
| S1 (2022–2024)           | 47 / 49                      | 1,741 / 797                     | 5 × 20 m                            | 44.5°/45.6°                       | 345.8°/194.2°                       |
| R2 (2016–2018)           | 19 / 28                      | 15,472 / 34,642                 | 3 × 1 m                             | 48°/39.3°                         | 350.7°/189.9°                       |
| RCM (2022–2024)          | 70 / 49                      | 8,697 / 12,647                  | 3 × 1 m                             | 37.5°/39.2°                       | 351.4°/193.6°                       |

It is important to note that the Sentinel-1 datasets for the two time periods (2016–2018 and 2022–2024) are derived from a single continuous PS-InSAR analysis covering the full 2016–2024 interval. The results are subsequently divided into two subsets to enable comparison with RADARSAT-2 and RCM datasets over corresponding time ranges. As a result, the spatial distribution of persistent scatterers remains consistent across the two Sentinel-1 subsets, while the temporal coverage differs.

These differences result in variations in spatial sampling, temporal coverage and measurement density across the datasets. Rather than attempting to standardize these differences, they are intentionally retained to evaluate the performance of the proposed framework under realistic multi-satellite conditions. This allows the analysis to examine how anomaly detection and spatial interpretation behave across datasets with different viewing geometries, which is essential for reliable multi-satellite bridge monitoring.

### 5.3. STUDY AREA AND DATA

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#### 5.3.3 DATA CHARACTERISTICS AND CHALLENGES

The multi-satellite dataset described in Section 5.3.2 provides a comprehensive set of observations for analyzing bridge deformation; however, it also introduces several challenges that must be carefully considered. These challenges arise primarily from differences in satellite characteristics, spatial sampling and acquisition geometry, which directly affect the interpretation of PS-InSAR results.

One of the main differences across the datasets is the variation in persistent scatterer (PS) density. As shown in Table 5.1, Sentinel-1 produces relatively sparse PS coverage over the bridge, while RADARSAT-2 and RCM provide significantly denser spatial sampling due to their higher resolution. This variation influences the level of detail that can be captured in the displacement field, with higher-density datasets enabling more continuous representation of structural behavior. In contrast, lower-density datasets may result in fragmented or localized measurements, making it more difficult to identify consistent spatial patterns.

In addition to spatial sampling, differences in temporal coverage and acquisition frequency also play an important role. The number of scenes varies across satellites and passes, leading to differences in temporal resolution and observation continuity. These variations can affect the stability of extracted displacement time series and the reliability of derived features, particularly in anomaly detection tasks where temporal consistency is critical.

Another important factor is the variation in acquisition geometry, including differences in incidence angle and satellite track direction. Since PS-InSAR measurements are obtained along the line-of-sight (LOS) direction, the observed displacement depends on the viewing geometry of each satellite. As a result, measurements from different satellites may capture different components of the actual structural motion, which can lead to discrepancies in the observed displacement behavior across datasets.

Furthermore, the spatial distribution of PS points is inherently irregular and influenced by surface characteristics. In the case of the Victoria Bridge, the surrounding water body leads to low coherence in SAR imagery, limiting the availability of reliable scatterers to structural elements



### 5.3. STUDY AREA AND DATA

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such as trusses and deck components. This results in uneven spatial coverage along the bridge, with certain regions having significantly higher PS density than others.

These differences in spatial sampling, temporal coverage and acquisition geometry introduce inconsistencies across datasets, making direct comparison of anomaly detection results challenging. In particular, variations in PS density and measurement sensitivity may lead to differences in the identification and spatial distribution of anomalous points, even when observing the same structural behavior.

To address these challenges, the proposed framework introduces a spatially structured representation of anomaly patterns and a set of normalization and comparison strategies designed to enable consistent interpretation across datasets. By organizing PS observations along the bridge axis and evaluating anomaly behavior at the zone level, the framework reduces the impact of irregular spatial sampling. In addition, the use of relative anomaly measures and cross-satellite agreement metrics provides a basis for comparing results across datasets with different characteristics.

#### 5.3.4 PS-IN SAR PROCESSING WORKFLOW

The processing framework follows established PSI principles, in which complex SAR images acquired at different times are combined into interferograms, and point-like coherent targets, persistent scatterers, are identified and tracked through time to produce displacement time series. For the RADARSAT-2 dataset covering the 2016–2018 period, scenes were acquired in Spotlight-A (SLA) beam mode, which provides the satellite’s highest ground spatial resolution (approximately  $3\text{ m} \times 1\text{ m}$ ) and is best suited for bridge monitoring applications [88, 90]. Two image stacks with opposite viewing geometries were processed: the SLA26 ascending stack, looking east with a  $48^\circ$  incidence angle, and the SLA12 descending stack, looking west with a  $39^\circ$  incidence angle. For each stack, a linear phase model was fitted to the PSI data using regression analysis to estimate residual height, linear time rate of displacement (mm/year) and coherence. The Sentinel-1 data spanning 2016–2024 were processed using the same PS-InSAR approach, with

#### 5.4. *ANOMALY DETECTION FRAMEWORK*

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acquisitions every 6 to 12 days providing dense temporal sampling but at a coarser spatial resolution ( $5 \times 20$  m) compared to the RADARSAT missions. The RCM dataset for 2022–2024 was processed at the same high spatial resolution as RADARSAT-2, with ascending and descending stacks providing complementary viewing geometries at incidence angles of approximately  $37^\circ$  and  $39^\circ$ , respectively (Table 5.1). A key challenge in the processing of bridge-specific PSI data is the combination of geometric effects, including layover, shadowing and multi-bounce reflections from structural elements and the surrounding water surface, that can complicate the identification of coherent targets. Because the Victoria Bridge is narrow and surrounded by the St. Lawrence River, persistent scatterers are predominantly concentrated on structural elements such as steel trusses, deck components, and railings, which act as strong natural reflectors. A backscatter analysis combined with a review of bridge construction drawings was used to associate radar returns with specific structural components and to identify and exclude obvious anomalous returns due to layover or multi-bounce effects. Following PS candidate selection, atmospheric phase contributions were estimated and removed, and displacement time series were extracted for each coherent target. Only targets maintaining high temporal coherence throughout the observation period were retained for the final displacement time series used in this study. The output of this processing workflow, displacement time series and velocity forms the input to the anomaly detection and spatial analysis framework described in the following sections. The present study focuses on modeling anomalous structural behavior within these processed PS-InSAR datasets, using unsupervised machine learning and spatially structured interpretation to identify persistent scatterers whose temporal displacement behavior deviates from the dominant structural response across multi-satellite observations.

## 5.4 ANOMALY DETECTION FRAMEWORK

The anomaly detection framework is based on established approaches for PS-InSAR time-series analysis and unsupervised anomaly detection, including Isolation Forest and feature-based representations of displacement behavior [48, 117]. The displacement time series obtained from

#### 5.4. ANOMALY DETECTION FRAMEWORK

PS-InSAR analysis are represented using a set of statistical and temporal features designed to capture different aspects of structural response. These features provide a compact and informative description of the displacement patterns at each persistent scatterer and form the basis for subsequent anomaly detection. An overview of the anomaly detection and spatial analysis workflow is shown in Figure 5.2.

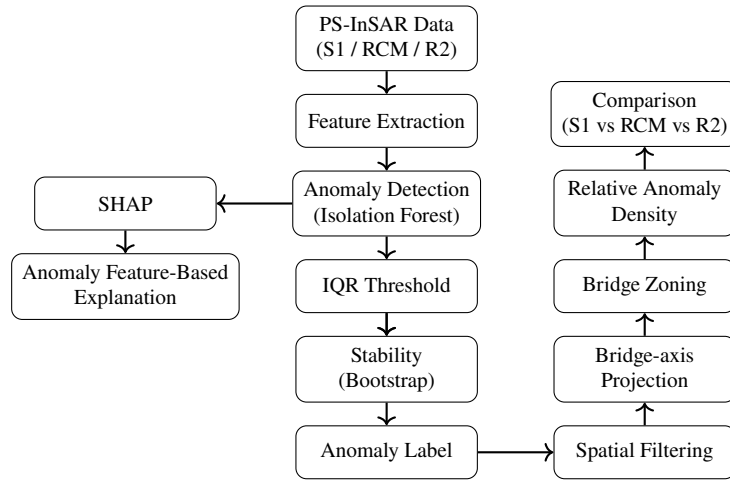


Figure 5.2: Overview of the proposed framework, including anomaly detection, spatial analysis and cross-satellite comparison.

##### 5.4.1 FEATURE REPRESENTATION OF DISPLACEMENT TIME SERIES

Each PS-InSAR displacement time series was represented using a set of statistical and temporal features selected to capture complementary aspects of structural behavior. The selected features describe the long-term displacement trends, displacement variability, temporal persistence, asymmetry of the signal and sensitivity to environmental effects. The specific features selected and their statistical properties are described in detail in Table 5.2. Together, they provide a compact but informative representation of the displacement response at each persistent scatterer.

The selected feature set includes all those as defined in Table 5.2. These features were chosen to balance physical interpretability and statistical diversity while avoiding excessive redundancy

#### 5.4. ANOMALY DETECTION FRAMEWORK

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Table 5.2: Selected features used for anomaly detection and their interpretation.

| Feature                 |                     | Description and Relevance                                                                                                                                                          |
|-------------------------|---------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Velocity                |                     | Long-term displacement rate, representing gradual deformation trends along the bridge deck.                                                                                        |
| Displacement            | Thermal Sensitivity | Measures the displacement response per °C, linking structural behavior directly to temperature variations.                                                                         |
| Displacement            | Drift Ratio         | Quantifies gradual non-stationary drift in the displacement time series, helping identify persistent deviation from the dominant structural response.                              |
| Trend Strength          |                     | Measures the degree to which a long-term displacement trend dominates the time series, making it useful for identifying consistent directional deformation.                        |
| Autocorrelation (Lag 1) |                     | Indicates temporal persistence in the displacement signal. High values suggest stable and predictable motion, whereas lower values indicate irregular or transient behavior.       |
| Offset Ratio            |                     | Captures abrupt displacement shifts or offset changes in the time series relative to its overall variation, which may indicate localized anomalies or measurement inconsistencies. |
| Absolute Displacement   | Median              | Represents the characteristic magnitude of displacement regardless of sign, highlighting points with unusually large overall movement.                                             |
| Skewness                |                     | Describes asymmetry in the displacement distribution, revealing bias toward one-sided motion or irregular displacement behavior.                                                   |
| Kurtosis                |                     | Measures the presence of extreme values in the displacement series. High kurtosis may indicate intermittent structural anomalies or abrupt displacement events.                    |

#### 5.4. ANOMALY DETECTION FRAMEWORK

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among highly correlated variables. In particular, velocity and trend strength describe gradual directional behavior, while features such as lag-1 autocorrelation, drift ratio and offset ratio capture temporal structure and deviations in the time series. Thermal sensitivity quantifies the relationship between displacement and temperature, which is especially relevant for bridge structures influenced by seasonal thermal expansion. The remaining features describe the magnitude and distributional shape of the displacement time series, enabling the identification of points with unusually large, asymmetric, or heavy-tailed behavior.

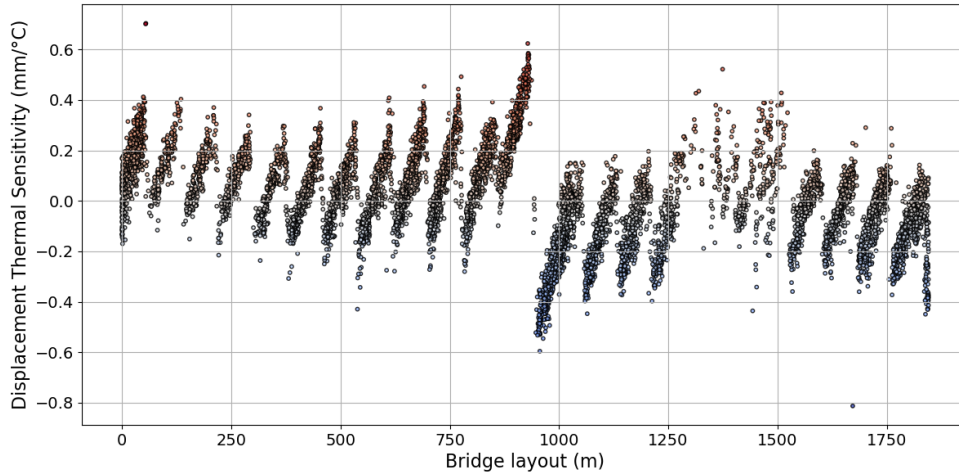


Figure 5.3: Spatial distribution of displacement thermal sensitivity along the bridge for the RCM descending dataset.

The spatial distribution of thermal sensitivity values along the bridge is illustrated in Figure 5.3, using the RCM descending dataset as a representative example. The figure shows that thermal response is not uniform along the bridge deck, but instead exhibits spatially varying patterns that reflect the thermal behavior in the longitudinal direction imposed by the connection type between the deck spans and the supporting piers. For example, the most negative or positive displacements are at expansion joints, while near zero displacements are at fixed locations. Thus, the spatially varying patterns reflect the differences in structural behavior, boundary conditions and local environmental influences, in particular, segments of the bridge display consistent positive or negative thermal sensitivity, indicating differential expansion and contraction behavior

## 5.4. ANOMALY DETECTION FRAMEWORK

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along the span. This spatial variability highlights the importance of including thermal sensitivity as a feature in the anomaly detection framework, as it captures physically meaningful variations that cannot be explained by purely statistical descriptors.

### 5.4.2 ANOMALY DETECTION

Anomaly detection algorithm used in structural health monitoring aims to identify persistent scatterers whose temporal displacement behavior deviates from the dominant trend. In this study, anomaly detection is performed using the Isolation Forest algorithm [48], which is an ensemble-based unsupervised method that exploits the principle that anomalous observations are few and structurally different from most of the data. Unlike density- or distance-based detectors, Isolation Forest does not model the normal class explicitly; instead, it isolates observations by recursively partitioning the feature space, and anomalies are identified as points that require fewer partitions to be separated from the rest of the dataset.

#### ISOLATION TREE CONSTRUCTION

An Isolation Forest is an ensemble of  $T$  binary trees, each referred to as an Isolation Tree (iTree). Given a dataset  $\mathbf{X} = \{\mathbf{x}_1, \dots, \mathbf{x}_n\} \subset \mathbb{R}^p$ , where  $n$  is the number of PS points and  $p$  is the number of features, each iTree is constructed by the following recursive procedure:

- (i) A sub-sample of size  $\psi \ll n$  is drawn without replacement from  $\mathbf{X}$ .
- (ii) A feature  $q \in \{1, \dots, p\}$  is selected at random.
- (iii) A split value  $s$  is drawn at random from the interval  $[\min(q), \max(q)]$  of the current node.
- (iv) Observations with  $x^{(q)} < s$  are routed to the left child node; the remaining observations are routed to the right child node.
- (v) Steps (2) to (4) are repeated recursively until each leaf contains a single observation or the tree reaches a maximum depth of  $\lceil \log_2 \psi \rceil$ .

#### 5.4. ANOMALY DETECTION FRAMEWORK

Because anomalies are sparse and structurally distinct, they tend to be isolated near the root of the tree after only a few splits, yielding a short path length  $h(\mathbf{x})$ , defined as the number of edges traversed from the root to the terminal leaf node. Normal observations, residing in dense regions of the feature space, require more splits and therefore produce longer path lengths (Figure 5.4).

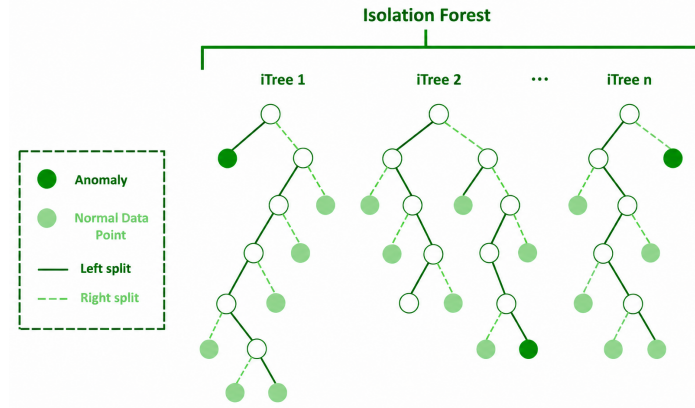


Figure 5.4: Isolation Forest tree for anomaly detection.

#### ANOMALY SCORE

To enable comparison among PS points and support the interpretation of their relative abnormality, an anomaly score was assigned to each point. Let  $h(\mathbf{x})$  denote the path length of observation  $\mathbf{x}$  in a single iTree. The expected path length  $\mathbb{E}[h(\mathbf{x})]$  is averaged over all  $T$  trees. To make path lengths comparable across sub-samples of different sizes, Liu et al. [48] normalise by the expected path length of an unsuccessful search in a Binary Search Tree (BST) of  $n$  nodes:

$$c(n) = 2 H(n - 1) - \frac{2(n - 1)}{n}, \quad (5.1)$$

where  $H(i) = \ln(i) + 0.5772$  is the  $i$ -th harmonic number approximated via the Euler–Mascheroni constant. The normalized anomaly score for observation  $\mathbf{x}$  is then defined as:

$$s(\mathbf{x}, n) = 2^{-\mathbb{E}[h(\mathbf{x})] / c(n)}. \quad (5.2)$$

#### 5.4. ANOMALY DETECTION FRAMEWORK

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The anomaly score can take values between 0 and 1:  $s(\mathbf{x}, n) \in (0, 1)$ . A score close to unity indicates that the observation is consistently isolated early across trees and is therefore likely anomalous. A score near 0.5 indicates no distinguishable isolation profile from the bulk of the PS points data, and a score significantly below 0.5 is characteristic of dense-region, normal observations.

##### ADAPTIVE ANOMALY LABELLING

Rather than relying on the default contamination-based threshold of the Isolation Forest model, an adaptive data-driven labeling procedure is applied. The anomaly scores are first standardized using a robust  $z$ -score based on the median and median absolute deviation (MAD):

$$\tilde{z}_i = \frac{s_i - \text{median}(\mathbf{s})}{\text{MAD}(\mathbf{s})}, \quad (5.3)$$

where  $\mathbf{s} = \{s_1, \dots, s_n\}$  is the vector of anomaly scores and  $\text{MAD}(\mathbf{s}) = \text{median}(|\mathbf{s} - \text{median}(\mathbf{s})|)$ . An adaptive threshold is then defined using the interquartile range (IQR) rule applied to the robust  $z$ -scores. A PS point is classified as anomalous if its score satisfies:

$$\tilde{z}_i < \tau, \quad \tau = Q_1 - 1.5 \times \text{IQR}, \quad (5.4)$$

where  $Q_1$  is the first quartile and  $\text{IQR} = Q_3 - Q_1$  of the robust  $z$ -scores. This approach avoids dependence on a pre-specified contamination level (i.e., the expected proportion of anomalies in the dataset) and allows the threshold to adapt to the empirical distribution of the data, which is particularly important given the variability of the PS density and temporal characteristics from the six satellite pass datasets investigated.

##### BOOTSTRAP STABILITY ANALYSIS

The stochastic nature of Isolation Forest, arising from random feature selection and random split value assignment, can produce variable anomaly labels across independent model runs. To



#### 5.4. ANOMALY DETECTION FRAMEWORK

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quantify and mitigate this instability, a bootstrap procedure is employed over  $B = 30$  independent runs. In each run  $b \in \{1, \dots, B\}$ , a new Isolation Forest model is fitted on a randomly selected subset containing a fraction  $f = 0.80$  of the PS points, and anomaly labels are assigned using the same adaptive IQR threshold (Eq. 5.4). The stability score of each PS point  $\mathbf{x}_i$  is defined as the fraction of runs in which it is classified as anomalous:

$$\text{Stab}(\mathbf{x}_i) = \frac{1}{B} \sum_{b=1}^B \mathbf{1}[\mathbf{x}_i \text{ labelled anomalous in run } b], \quad (5.5)$$

where  $\mathbf{1}[\cdot]$  is the indicator function. A PS point is retained as anomalous in the final consensus label set only if it satisfies both of the following conditions simultaneously:

- (i) It is classified as anomalous by the base Isolation Forest model using the adaptive threshold  $\tau$  defined in Eq. (5.4).
- (ii) Its stability score satisfies  $\text{Stab}(\mathbf{x}_i) \geq \delta$ , where  $\delta = 0.75$ .

This two-stage consensus criterion is used because it jointly enforces score-based significance and cross-run reproducibility, reducing the influence of model randomness and preventing spurious detections from propagating to the spatial analysis stage. The stability threshold  $\delta = 0.75$  was selected to retain only PS points classified as anomalous in at least 75% of the bootstrap runs, thereby ensuring that the final anomaly labels represent persistent and reproducible deviations rather than isolated detections caused by random sampling variability. Lower thresholds were found to admit unstable detections, whereas higher thresholds became overly restrictive and removed spatially coherent anomaly patterns. The choice of  $B = 30$  and  $f = 0.80$  represents a practical balance between computational cost and stability estimation accuracy; sensitivity analyses confirmed that the consensus labels were not materially affected by modest variations in these parameters.

#### MODEL PARAMETERS AND FEATURE SCALING

#### 5.4. ANOMALY DETECTION FRAMEWORK

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The base Isolation Forest model is configured with  $T = 300$  trees, a sub-sample size of  $\psi = 256$  observations per tree, and all  $p$  features used at each split. These settings follow the recommendations of Liu et al. [48], who demonstrate that the algorithm achieves stable performance with sub-sample sizes as small as  $\psi = 256$ , and that increasing  $T$  beyond a few hundred trees yields negligible improvements in score accuracy. Prior to model fitting, all features are standardised using a robust scaler based on the median and interquartile range:

$$\tilde{x}_{ij} = \frac{x_{ij} - \text{median}(\mathbf{x}_j)}{\text{IQR}(\mathbf{x}_j)}, \quad (5.6)$$

for each feature  $j \in \{1, \dots, p\}$ . This normalisation ensures that features with large absolute ranges, such as velocity (mm/yr), do not dominate the partitioning process over features with inherently smaller magnitudes, such as skewness or lag-1 autocorrelation. The use of median and IQR-based scaling, rather than mean and standard deviation, further reduces the influence of extreme values that may correspond to anomalous PS points.

The resulting consensus anomaly labels identify PS points that exhibit statistically significant and reproducible deviations in their temporal displacement behavior across the full feature space. These labels are subsequently passed to the spatial analysis framework described in Section 5.5, where they are refined through neighborhood consistency filtering and projected onto the longitudinal bridge axis for structural interpretation.

##### 5.4.3 INTERPRETATION OF ANOMALIES

To improve the interpretability of the anomaly detection results, SHAP (SHapley Additive exPlanations) was employed to quantify the contribution of each feature to the anomaly score at the level of individual persistent scatterers. SHAP is an explainable artificial intelligence method that quantifies the contribution of each feature to a model prediction. In this study, SHAP is used to identify which displacement characteristics most strongly influence the anomaly score of each PS point [53]. This approach enables a transparent understanding of how different characteristics of the displacement time series influence the classification outcome.

#### 5.4. ANOMALY DETECTION FRAMEWORK

Figure 5.5 presents a representative example of SHAP-based interpretation for a single PS point identified as anomalous in the RCM descending dataset. The SHAP values indicate that the anomaly score is primarily influenced by a combination of velocity and displacement variability, the latter captured through the absolute median displacement feature. Among these, thermal sensitivity exhibits a notable contribution, suggesting that the displacement behavior of this point is strongly influenced by temperature variations.

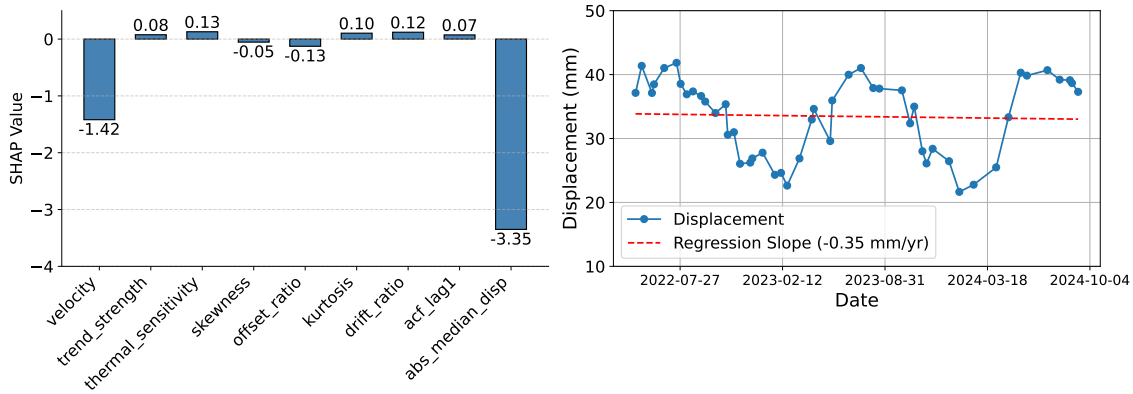


Figure 5.5: Representative SHAP-based interpretation of an anomalous PS point, showing feature contributions (left) and the corresponding displacement time series (right).

The corresponding displacement time series provides additional context for this behavior. The point exhibits noticeable fluctuations and a non-uniform temporal pattern, deviating from the smoother and more consistent responses typically observed in neighboring PS points. These variations are not characterized by extreme displacement magnitudes, but rather by differences in the evolution of the displacement signal over time, including changes in slope and irregular temporal behavior.

From a structural perspective, such behavior is consistent with the expected response of points located near the longitudinal free end of a simply supported span. In these regions, thermal expansion and contraction are less constrained, allowing larger and more variable displacement responses compared to points located closer to the supports or mid-span regions. As a result,

### 5.5. SPATIAL ANALYSIS FRAMEWORK

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these points may naturally exhibit stronger thermal sensitivity and increased variability in their displacement time series.

This example illustrates that the proposed framework does not rely solely on statistical deviation, but is capable of capturing physically meaningful variations in structural response. By combining SHAP-based interpretation with displacement time series analysis, the method provides insight into the underlying factors contributing to anomaly identification, linking data-driven detection with structural behavior.

## 5.5 SPATIAL ANALYSIS FRAMEWORK

While the anomaly detection framework described in Section 4 identifies persistent scatterers that exhibit abnormal temporal behavior, the resulting anomaly labels remain defined at the level of individual points. Due to the irregular spatial distribution of PS points and their dependence on coherence conditions, direct interpretation of these anomalies in a structural context is challenging. In particular, isolated point-wise anomalies may not reliably indicate meaningful structural patterns without considering their spatial organization.

To address this limitation, a spatial analysis framework is introduced to transform point-wise anomaly detection results into a structured representation aligned with the geometry of the bridge. The proposed framework enables the analysis of anomalies along the longitudinal direction of the structure, allowing the identification of spatial trends and localized regions of abnormal behavior.

The framework consists of several steps. First, anomaly detection is performed at the level of individual PS points using the approach described in Section 4, followed by a spatial consistency refinement step. In this step, isolated anomalies are removed based on their local neighborhood, resulting in a spatially filtered anomaly label that emphasizes clustered and structurally meaningful behavior.

Next, the refined PS points are projected onto a reference bridge axis to obtain a one-dimensional representation of their spatial location. The bridge is then divided into discrete

## 5.5. SPATIAL ANALYSIS FRAMEWORK

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zones along this axis, enabling spatial aggregation of anomaly information. To ensure reliability, zones with insufficient PS coverage are filtered out. Anomaly density is subsequently computed at the zone level and normalized to account for differences in PS distribution across datasets. Finally, the resulting spatial patterns are compared across the three satellites to assess consistency and agreement.

### 5.5.1 SPATIAL FILTERING OF ANOMALIES

The anomaly detection procedure described in Section 5.4 identifies abnormal temporal behavior at the level of individual persistent scatterers. However, due to the noise in measurement data, local decorrelation effects and variability in PS density, some detected anomalies may appear as isolated points that do not correspond to meaningful structural behavior of the bridge deck. Such isolated detections can reduce the reliability of interpretation, particularly in the context of infrastructure monitoring where structural responses are expected to exhibit spatial continuity.

To address this limitation, a spatial filtering step is added to refine the anomaly labels based on local spatial consistency. In this approach, an anomaly is retained only if it is supported by neighboring anomalous points within a predefined spatial radius. Specifically, for each PS point initially labeled as anomalous, the number of PS anomalous neighbors within a fixed distance is evaluated. If this number is below a specified threshold, the point is excluded from the set of spatially coherent anomalies used for subsequent spatial analysis. This filtering process effectively removes isolated detections while preserving clusters of anomalies that are more likely to represent structurally meaningful behavior.

The selection of spatial filtering parameters is guided by the empirical spatial distribution of the PS points. Figure 5.6 illustrates the distribution of nearest-neighbor spacing for different descending datasets from S1, RCM and R2 satellites. Based on this distribution, the neighborhood radius is defined as approximately three times the median of the PS spacing, ensuring that the spatial filter captures local clusters while remaining consistent with the intrinsic measurement density of each dataset. In addition to the spatial radius, a minimum requirement of two neighboring anomalous points within this radius is imposed. This criterion ensures that anomalies are

### 5.5. SPATIAL ANALYSIS FRAMEWORK

retained only when they form small spatial clusters, thereby reducing the influence of isolated detections while preserving localized structural patterns.

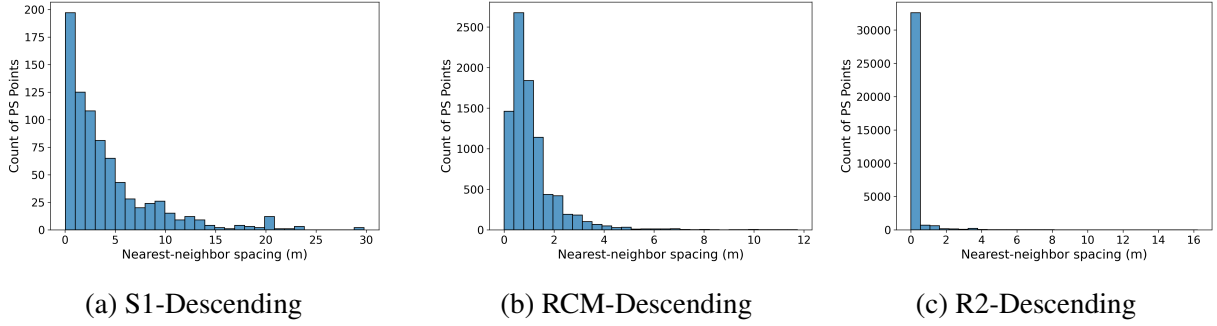


Figure 5.6: Distribution of nearest-neighbor spacing between PS points for different satellite descending datasets.

Figure 5.6 also highlights important differences in the spatial distribution of PS points across the three satellite datasets. For the Sentinel-1 dataset (Figure 5.6a), the histogram shows a strong peak near zero followed by a gradual decrease, indicating that many PS points are relatively close to each other while larger separations occur less frequently. This behavior is consistent with a sparse but non-uniform PS distribution along the bridge. In contrast, the RCM dataset (Figure 5.6b) shows its highest frequency slightly away from zero, suggesting a more regular spacing between neighboring PS points. The R2 dataset (Figure 5.6c) contains fewer visible histogram bins because the very high PS density causes most nearest-neighbor distances to concentrate within a narrow range close to zero. Together, these distributions illustrate how PS density and spatial sampling differ between satellites, which directly influences the selection of spatial filtering parameters.

The spatial filtering procedure corresponds to a neighborhood-based consistency check, where both the neighborhood radius and the minimum number of required neighbors are adapted to each satellite dataset based on its PS density characteristics. This adaptive formulation ensures that the filtering process remains consistent across datasets with different spatial resolutions and measurement distributions. The resulting refined anomaly labels are referred to as spatial labels, which represent anomalies that are both temporally abnormal (as identified by the anomaly detection

## 5.5. SPATIAL ANALYSIS FRAMEWORK

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model) and spatially consistent. This distinction is important, as it shifts the interpretation from point-wise outliers to spatially coherent patterns along the bridge deck structure.

The spatially filtered anomaly labels form the basis for all subsequent spatial analyses, including bridge-axis projection, zoning and anomaly density estimation. By ensuring that only spatially consistent anomalies are considered, the proposed framework enhances the robustness and interpretability of the results at the structural level.

### 5.5.2 BRIDGE-AXIS PROJECTION AND ZONING

Following the spatial filtering step, the anomaly detection results are represented as spatially consistent PS points distributed across the bridge deck surface. However, these points remain defined in a two-dimensional cartesian coordinate system, which makes it difficult to directly interpret structural behavior along the longitudinal direction of the bridge.

To enable a structurally meaningful analysis, i.e., to be able to associate the measured PS points to the displacements of the deck, the PS points are projected onto a one-dimensional reference axis aligned with the bridge. This bridge-axis projection transforms the spatial coordinates of each PS point into a scalar distance along the bridge, allowing all measurements to be analyzed in a consistent longitudinal framework. The bridge axis is defined as a straight line connecting the endpoints of the bridge, corresponding to its primary longitudinal direction. All PS points are first converted into a projected coordinate system to ensure accurate distance calculations. Each point is projected onto the bridge axis along the satellite line-of-sight (LOS) direction, defined as the satellite heading plus  $90^\circ$  (Figure 5.7). This approach ensures that the projection is consistent with the radar acquisition geometry, as InSAR measurements inherently represent displacement along the LOS direction.

For each PS point, a line oriented along the LOS direction is constructed, and its intersection with the bridge axis determines the projected location. An example of the LOS-based projection is illustrated in Figure 5.7b, where  $A$  and  $B$  denote the original PS point locations and  $A'$  and  $B'$  represent their projected positions on the bridge axis. The projection is performed along the

## 5.5. SPATIAL ANALYSIS FRAMEWORK

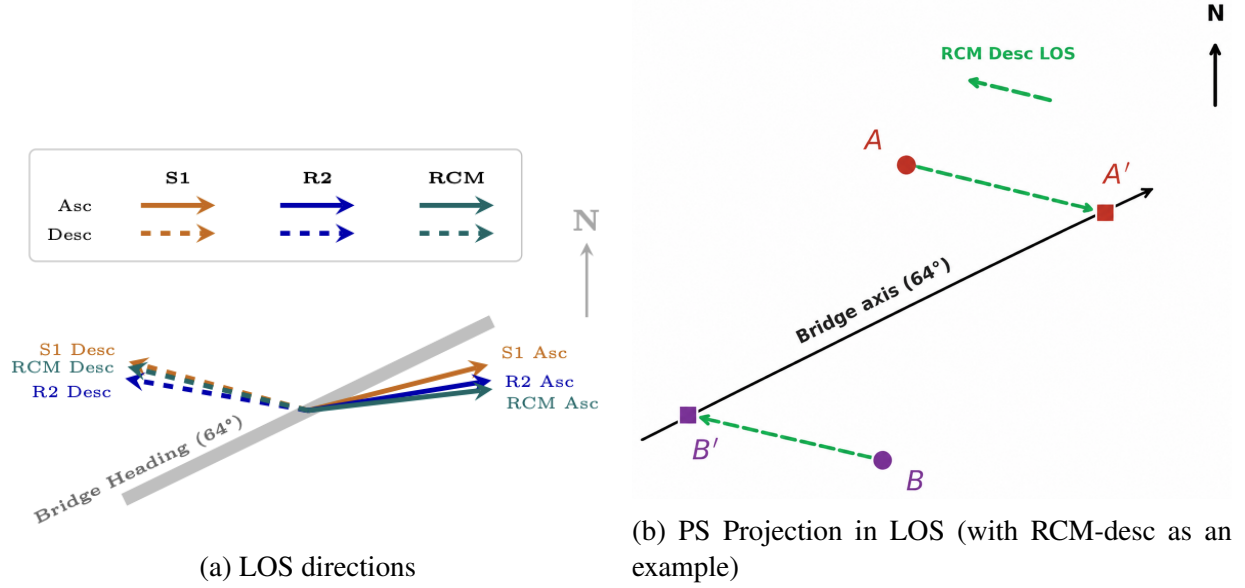


Figure 5.7: LOS projection for each satellite and pass geometry relative to the Victoria Bridge heading.

LOS direction associated with the satellite acquisition geometry (shown for the RCM descending pass), ensuring that the projected locations remain consistent with the physical SAR observation direction. The position of the point is then expressed as the distance from the reference origin at the left (West) end of the bridge (in this case). This transformation reduces the spatial complexity of the dataset while preserving the physically meaningful positioning of PS points along the structure.

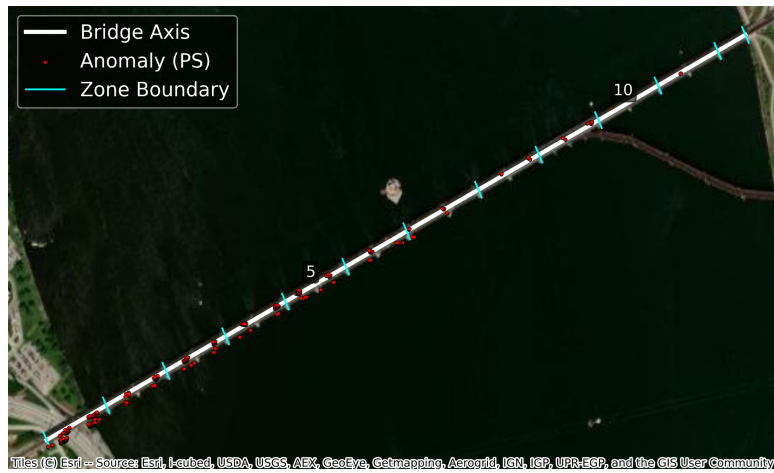
To further analyze the structure, the bridge axis is divided into a set of discrete zones defined by non-uniform boundaries along its length. Each zone represents a segment of the bridge over which PS points and anomalies can be aggregated. This zoning strategy enables the transition from point-wise analysis to segment-level interpretation, which is more consistent with structural engineering practice. Instead of adopting equal-length segmentation, the boundaries are selected to approximately correspond to every two structural spans of the bridge (with the exception of zone 9, which includes the 4 shorter spans), resulting in variable zone lengths that reflect the underlying structural configuration (Figure 5.8). This approach allows the zoning scheme



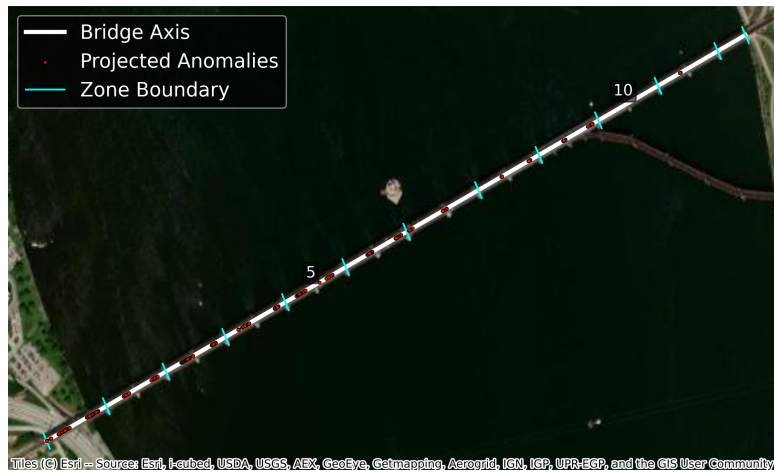


## 5.5. SPATIAL ANALYSIS FRAMEWORK

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(a) Before Projection



(b) After Projection

Figure 5.9: Spatial distribution of bridge-axis zones and detected anomalies for the RCM descending dataset: (a) original PS locations and (b) LOS-projected PS locations along the bridge axis.

### 5.5. SPATIAL ANALYSIS FRAMEWORK

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distribution along the structure. This aggregation transforms point-wise anomaly information into a segment-based representation that is more consistent with structural assessment practices.

For each bridge zone, the anomaly density is defined as the ratio of anomalous PS points to the total number of PS points within that zone. Formally, for a given zone  $z$ , the anomaly density is defined as:

$$D_z = \frac{N_z^{\text{anomaly}}}{N_z^{\text{total}}} \quad (5.7)$$

where  $N_z^{\text{anomaly}}$  denotes the number of PS points labeled as anomalous based on the spatial label, and  $N_z^{\text{total}}$  represents the total number of PS points within the zone. This formulation provides a normalized measure of anomaly concentration that accounts for variations in PS availability along the bridge.

To ensure statistical reliability, zones with insufficient PS coverage are excluded from the current analysis. Specifically, zones containing fewer than a minimum number of PS points are filtered out prior to anomaly density computation. This step mitigates instability in estimating the density that may arise from small sample sizes and ensures that the resulting metrics reflect reliable spatial patterns.

Although anomaly density provides a useful measure of local anomalies concentration, direct comparison across datasets from different satellites may be affected by differences in PS density, spatial resolution and acquisition characteristics. To address this limitation, a relative anomaly density is introduced to normalize the zone-level density with respect to the overall anomaly level of the dataset.

The global anomaly density for a given dataset is defined as:

$$D_{\text{global}} = \frac{\sum_z N_z^{\text{anomaly}}}{\sum_z N_z^{\text{total}}} \quad (5.8)$$

## 5.5. SPATIAL ANALYSIS FRAMEWORK

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The relative anomaly density for each zone is then computed as:

$$R_z = \frac{D_z}{D_{\text{global}}} \quad (5.9)$$

This normalization removes the influence of global anomaly rates and enables meaningful comparison of anomaly patterns across datasets with different PS distributions. As a result, zones with  $R_z > 1$  indicate higher-than-average anomaly concentration, while zones with  $R_z < 1$  correspond to relatively lower anomaly activity.

### 5.5.4 CROSS-SATELLITE AGREEMENT ANALYSIS

To assess the consistency of anomaly detection results across different satellite datasets, a comparative analysis is conducted based on the ranking of bridge zones derived from their relative anomaly density (Section 5.5.3). Two complementary metrics are employed: (i) Top- $K$  overlap, which quantifies agreement in identifying the most anomalous zones, and (ii) Spearman rank correlation [118], which evaluates the similarity of the full zone ranking between satellite datasets.

#### ZONE RANKING

For a given dataset  $d$ , each bridge zone  $z \in \{1, \dots, Z\}$  is assigned a rank  $r_d(z)$  based on its relative anomaly density  $R_z^{(d)}$  (Eq. 5.9), where rank 1 corresponds to the zone with the highest relative anomaly density. Zones excluded due to insufficient PS coverage are omitted from the ranking. The resulting ranked list  $\mathbf{r}_d = (r_d(1), \dots, r_d(Z))$  provides a dataset-specific ordering of bridge zones by anomaly concentration, enabling structured comparison across satellites.

#### TOP- $K$ OVERLAP

The Top- $K$  overlap between datasets  $d_1$  and  $d_2$  is defined as the proportion of shared zones among

### 5.5. SPATIAL ANALYSIS FRAMEWORK

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their respective top- $K$  sets, normalized by  $K$  [119]. Let  $\mathcal{T}_K^{(d)}$  denote the set of the top- $K$  zones for dataset  $d$ , defined as:

$$\mathcal{T}_K^{(d)} = \{z \mid r_d(z) \leq K\}. \quad (5.10)$$

The Top- $K$  overlap between datasets  $d_1$  and  $d_2$  is then defined as the Jaccard-style intersection ratio:

$$\text{Overlap}_K(d_1, d_2) = \frac{|\mathcal{T}_K^{(d_1)} \cap \mathcal{T}_K^{(d_2)}|}{K}, \quad (5.11)$$

where  $|\cdot|$  denotes set cardinality. This metric ranges from 0, indicating no shared zones among the top- $K$ , to 1, indicating perfect agreement. Multiple values of  $K \in \{3, 5, 7\}$  were evaluated to examine the sensitivity of cross-satellite agreement to the number of selected anomalous zones. It was observed that the level of agreement increased with  $K$ , with larger values yielding more stable overlap estimates. Based on this analysis,  $K = 7$  was selected as the representative case for the results presented in Section 5.6.

### SPEARMAN RANK CORRELATION

While Top- $K$  overlap captures agreement among the most anomalous zones, it provides no information about the consistency of the full zone ranking. To address this, the Spearman rank correlation coefficient [118] is computed between the ranked anomaly density profiles of each pair of datasets. Given two ranked vectors  $\mathbf{r}_{d_1}$  and  $\mathbf{r}_{d_2}$  over  $M$  mutually observed zones, the Spearman correlation is defined as:

$$\rho_s(d_1, d_2) = 1 - \frac{6 \sum_{z=1}^M d_z^2}{M(M^2 - 1)}, \quad (5.12)$$

## 5.6. RESULTS AND DISCUSSION

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where  $d_z = r_{d_1}(z) - r_{d_2}(z)$  is the rank difference for zone  $z$ . Equation (5.12) is the standard closed-form expression for Spearman's  $\rho$  in the absence of tied ranks [118]. In practice, tied ranks can arise when two zones share identical relative anomaly density values; in such cases, average ranks are assigned and the full Pearson correlation formula applied to the rank vectors is used instead:

$$\rho_s(d_1, d_2) = \frac{\sum_{z=1}^M (r_{d_1}(z) - \bar{r}_{d_1})(r_{d_2}(z) - \bar{r}_{d_2})}{\sqrt{\sum_{z=1}^M (r_{d_1}(z) - \bar{r}_{d_1})^2} \sqrt{\sum_{z=1}^M (r_{d_2}(z) - \bar{r}_{d_2})^2}}, \quad (5.13)$$

where  $\bar{r}_{d_1}$  and  $\bar{r}_{d_2}$  are the mean ranks over the  $M$  zones for datasets  $d_1$  and  $d_2$ , respectively. The coefficient  $\rho_s \in [-1, 1]$ , where  $\rho_s = 1$  indicates perfect rank agreement,  $\rho_s = -1$  indicates a perfectly reversed ordering, and  $\rho_s = 0$  indicates no monotonic relationship between the zone rankings of the two compared datasets.

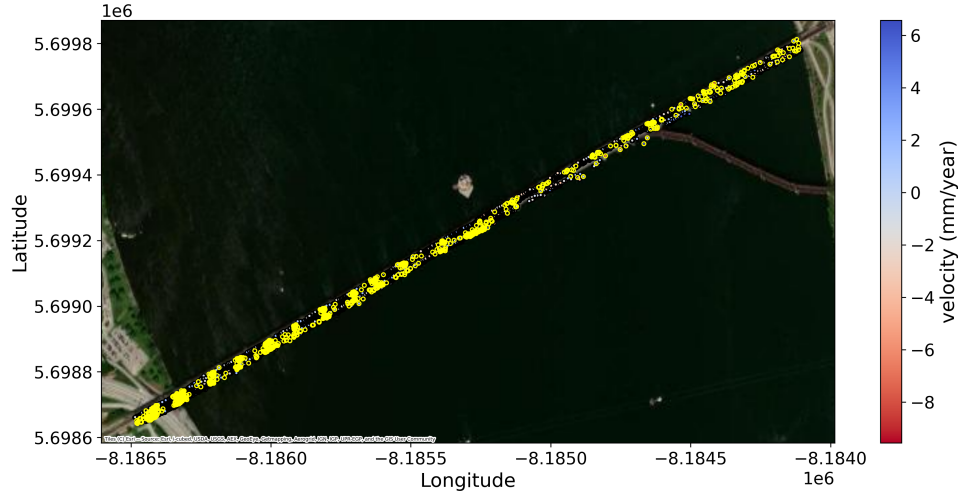
## 5.6 RESULTS AND DISCUSSION

### 5.6.1 SPATIAL REFINEMENT OF ANOMALY DETECTION RESULTS

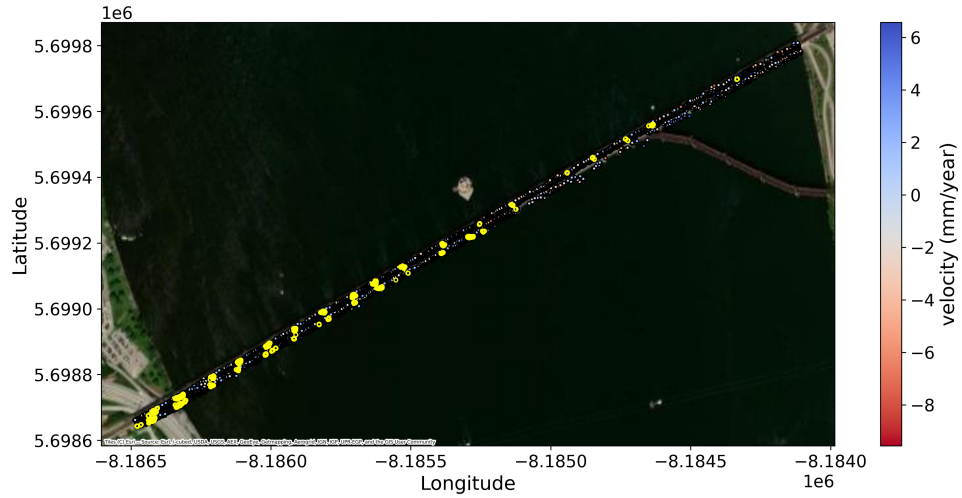
Following the anomaly detection analysis, described in section 5.4, the anomaly detection results for the RCM descending dataset are first examined at the level of individual PS points. As shown in Figure 5.10a, the detected anomalies are scattered along the bridge, with a mixture of isolated points and small clusters. This distribution makes it difficult to distinguish between meaningful structural patterns and noise-driven detections. After applying the spatial filtering step, described in section 5.5 the anomalous points distribution becomes more coherent (Figure 5.10b). Isolated detections are largely removed and anomalies appear in localized clusters, indicating regions where neighboring anomalous PS points exhibit consistent behavior. This leads to a clearer spatial pattern along the bridge.

## 5.6. RESULTS AND DISCUSSION

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(a) Initial anomaly detection results (consensus labels).



(b) Spatially filtered anomaly results (spatial labels).

Figure 5.10: Comparison of anomaly detection results for the RCM descending dataset before and after spatial filtering.

## 5.6. RESULTS AND DISCUSSION

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To further interpret these patterns, the filtered results are analyzed along the bridge axis using the zoning framework introduced in Section 5.5.2 (see Figure 5.9). This representation allows anomalies to be examined as a function of structural position, providing a more interpretable view of their distribution.

Table 5.3 shows that spatial filtering substantially reduces the number of retained anomalous PS points across all datasets, confirming that many initial detections are spatially isolated. The reduction is particularly pronounced for Sentinel-1, where the number of retained anomalies decreases to a small subset, reflecting its lower PS density and greater sensitivity to isolated detections. In contrast, RCM and RADARSAT-2 retain a larger number of anomalies after filtering, especially in the descending pass, suggesting stronger spatial clustering supported by denser PS coverage. These results indicate that spatial filtering does not affect all datasets uniformly; rather, its impact depends on satellite resolution, PS density, and acquisition geometry. Therefore, the filtered anomaly labels should be interpreted as spatially coherent anomaly candidates rather than a direct measure of damage occurrence.

Table 5.3: Number of anomalous PS points before and after spatial filtering for different satellites and acquisition passes.

| Satellite | Pass | Before | After | Ratio |
|-----------|------|--------|-------|-------|
| S1 (2016) | Desc | 71     | 13    | 0.18  |
| S1 (2016) | Asc  | 80     | 13    | 0.16  |
| S1        | Desc | 65     | 12    | 0.18  |
| S1        | Asc  | 87     | 16    | 0.18  |
| RCM       | Desc | 1063   | 599   | 0.56  |
| RCM       | Asc  | 678    | 245   | 0.36  |
| R2        | Desc | 1488   | 474   | 0.32  |
| R2        | Asc  | 634    | 187   | 0.29  |

Overall, spatial filtering and bridge-axis projection significantly improve the interpretability of anomaly detection results, enabling the identification of consistent regions of anomalous behavior rather than isolated point-wise detections. While the spatial filtering step improves the reliability



## 5.6. RESULTS AND DISCUSSION

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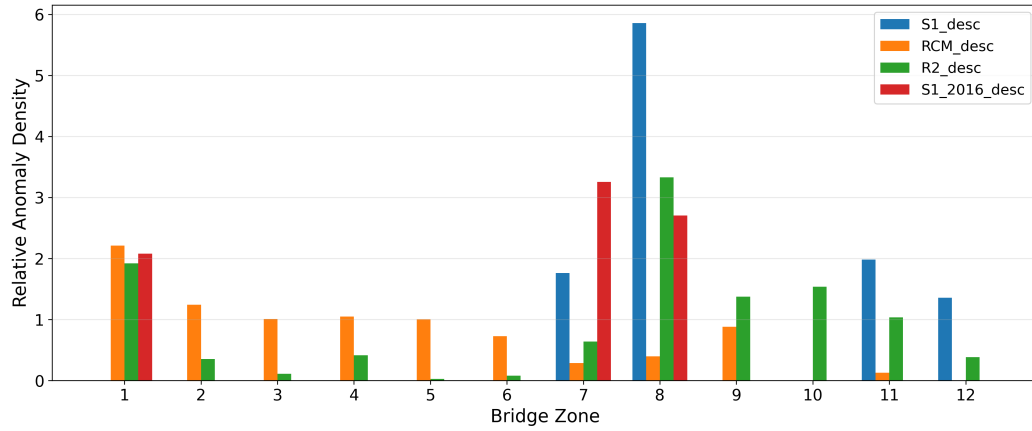
of point-level anomaly detection, the resulting anomaly labels alone do not fully capture how anomalous behavior is distributed along the bridge. In particular, isolated point detections, even after refinement, provide limited insight into whether anomalies form consistent spatial patterns or remain scattered. To address this, the bridge-axis zoning framework, described in section 5.5.2, is used to aggregate anomaly information along the bridge axis. This allows the interpretation to shift from individual PS points to spatially coherent regions, enabling a more meaningful comparison of anomaly patterns across different datasets.

### 5.6.2 SPATIAL DISTRIBUTION AND CROSS-SATELLITE CONSISTENCY OF ANOMALY PATTERNS

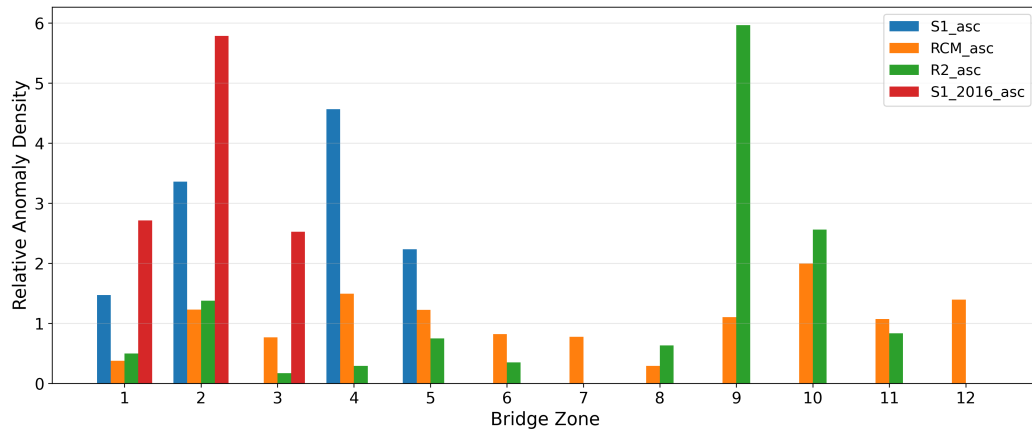
Building on the spatially refined anomaly labels, the anomaly information is aggregated along the bridge deck axis using the LOS-based projection and zoning strategy described in Section 5.5.2. This approach ensures that persistent scatterers are positioned along the bridge in a manner consistent with the radar acquisition geometry, providing a more physically meaningful basis for analyzing spatial patterns.

The relative anomaly density charts shown in Figure 5.11 indicate that anomaly patterns are not uniformly distributed along the bridge and that the spatial response varies considerably across satellites and acquisition geometries. For the descending datasets (Figure 5.11a), both Sentinel-1 and RADARSAT-2 dataset exhibit a pronounced anomaly concentration around Zones 7–8, corresponding approximately to bridge spans 13–16. This recurring peak represents the most spatially consistent anomaly-prone region observed across the datasets. In contrast, the RCM descending dataset shows a comparatively flatter profile with lower relative anomaly density variations, suggesting weaker spatial concentration of anomalies despite its relatively high PS density. The ascending datasets (Figure 5.11b) exhibit substantially lower consistency. Both Sentinel-1 ascending datasets show elevated anomaly density around Zone 2 (approximately spans 3–4), while the Sentinel-1 recent ascending dataset additionally presents a secondary peak around Zone 4. In contrast, the RADARSAT-2 ascending dataset reaches its dominant peak near Zone 9, and the RCM ascending dataset again shows relatively limited anomaly concentration

## 5.6. RESULTS AND DISCUSSION



(a) Descending Pass



(b) Ascending Pass

Figure 5.11: Relative anomaly density along the bridge axis for the three satellites.

## 5.6. *RESULTS AND DISCUSSION*

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along the bridge. These differences indicate that the spatial distribution of anomalies is strongly affected by acquisition geometry and sensor characteristics, particularly for ascending passes. An additional observation is that the Sentinel-1 datasets exhibit a clear directional dependence between ascending and descending acquisitions. For both the historical and recent Sentinel-1 datasets, the dominant anomaly concentrations in the descending passes are primarily located toward the eastern portion of the bridge, whereas the ascending passes show elevated anomaly density predominantly on the western side. This behavior suggests that the observed anomaly patterns are influenced not only by the structural response itself, but also by the LOS geometry of the SAR acquisitions. Since ascending and descending passes measure different displacement components, certain localized structural responses may become more pronounced depending on the viewing direction of the satellite. In contrast to the Sentinel-1 datasets, the RCM and RADARSAT-2 results do not exhibit a similarly clear east–west separation between ascending and descending passes. The RCM datasets show comparatively flatter anomaly profiles with weaker localized concentrations, while RADARSAT-2 exhibits sharper and more localized peaks that are not consistently mirrored across acquisition geometries. This suggests that the directional dependence observed in Sentinel-1 is less pronounced in the higher-resolution datasets, where local PS distribution and localized spatial variability appear to play a stronger role in shaping the anomaly patterns.

The LOS-based projection contributes to a more physically consistent spatial representation of the PS points by aligning the measurements with the SAR observation geometry. However, the results also show that geometric alignment alone is insufficient to achieve strong cross-satellite agreement. While some dominant anomaly-prone regions recur across multiple datasets, particularly for the descending acquisitions, the detailed shape, magnitude and ranking of anomaly distributions remain highly sensor-dependent. RADARSAT-2 generally produces sharper and more localized anomaly peaks, likely due to its denser PS coverage and higher spatial resolution, whereas Sentinel-1 produces broader and smoother profiles associated with lower PS density. Overall, the results suggest that agreement between satellites is more reliable at the level of dominant anomaly-prone regions than in the detailed spatial ranking of bridge zones.

## 5.6. RESULTS AND DISCUSSION

The cross-satellite agreement results provide additional insight into these patterns. The Top-7 overlap matrix (Figure 5.12) shows that several datasets identify a common subset of highly anomalous zones. This suggests that the framework is able to capture recurring spatial features that are not tied to a single satellite. However, the level of agreement varies across dataset pairs and is generally stronger among datasets with similar acquisition characteristics.

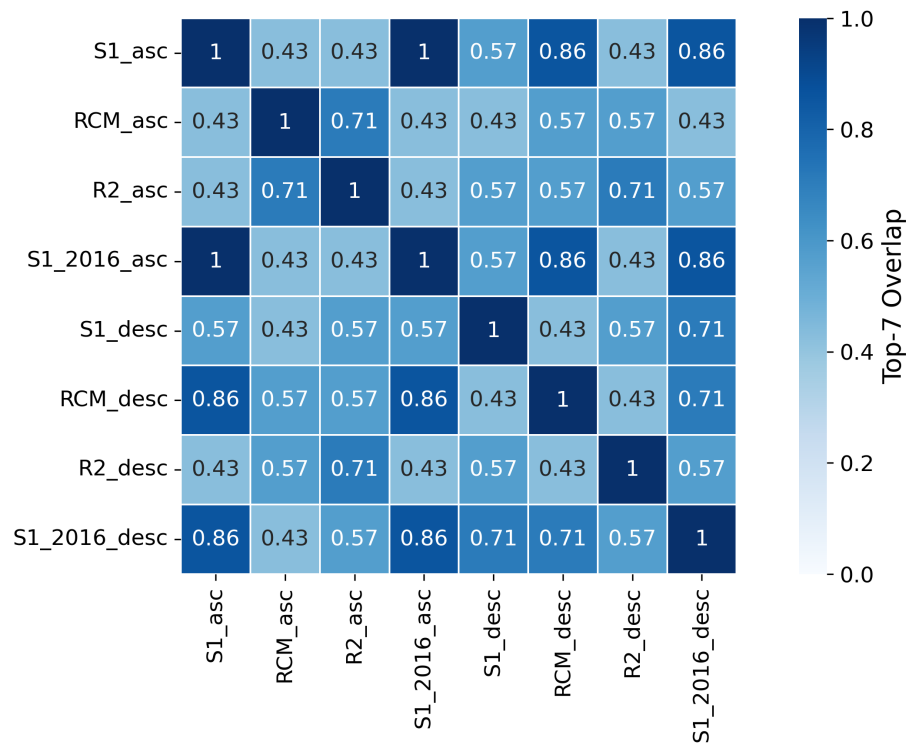


Figure 5.12: Top-7 overlap matrix showing the proportion of shared anomalous zones between datasets.

This variability becomes more apparent in the Spearman rank correlation results (Figure 5.13), where correlations range from moderate to weak, and in some cases are negative. These results indicate that, although satellites often agree on the presence of anomalous regions, they do not consistently agree on their relative importance. In other words, there is partial agreement in identifying key zones, but limited consistency in how those zones are ranked.

## 5.6. RESULTS AND DISCUSSION

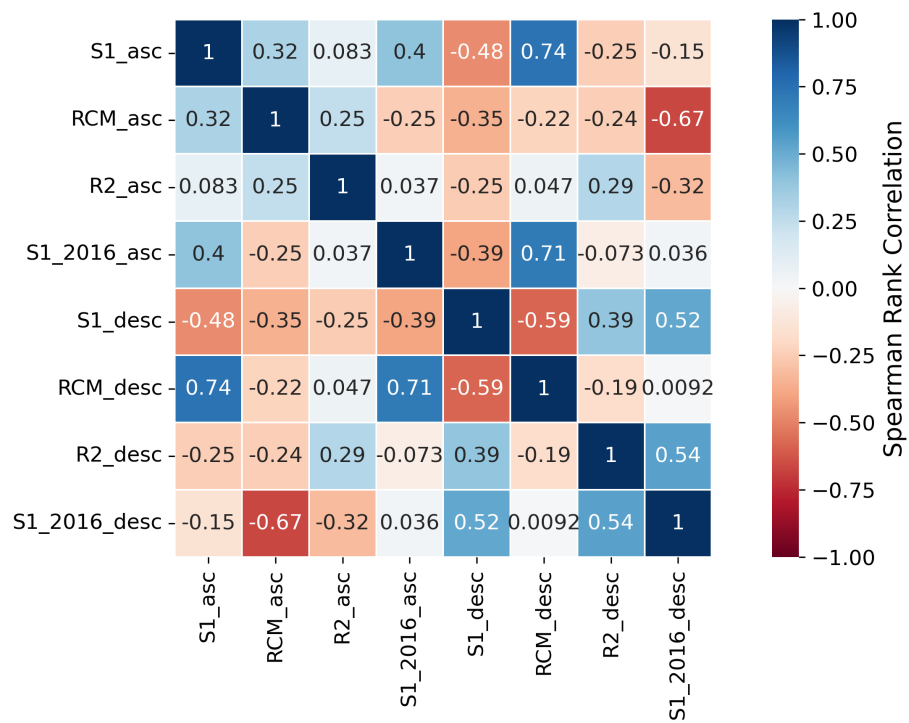


Figure 5.13: Spearman rank correlation matrix comparing the ordering of anomaly density across zones for different datasets.

## 5.6. RESULTS AND DISCUSSION

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The difference between Top-K overlap and rank correlation is therefore an important aspect of the results. The Top-7 overlap demonstrates that the framework can reliably identify the main anomaly-prone regions along the bridge. In contrast, the weaker rank correlations indicate that fine-scale prioritization is sensitive to satellite-specific factors and should be interpreted with caution.

Overall, the results show that the proposed spatial framework provides a clearer and more structured representation of anomaly patterns along the bridge. It enables meaningful comparison across datasets by focusing on spatial consistency rather than exact numerical agreement. At the same time, the remaining variability highlights the importance of interpreting multi-satellite PS-InSAR results in a comparative manner, emphasizing recurring spatial trends rather than expecting full agreement across satellites.

### 5.6.3 DISCUSSION

The anomaly concentrations identified in this study show a strong relationship with the structural configuration of the Victoria Bridge, suggesting that the proposed framework is capturing meaningful variations in structural response rather than random measurement noise. The most prominent and recurring anomaly concentration, observed across several satellite datasets, is located around Zones 7–9. From a structural perspective, this behavior is physically plausible. Span 13 in Zone 7 corresponds to the longest through-truss span on the bridge (109.6 m) and differs structurally from the surrounding deck truss spans in both geometry and load-transfer mechanism. Its greater length and lower longitudinal restraint make it more sensitive to thermal expansion and contraction, resulting in displacement histories that differ from the dominant bridge-wide response. Similarly, Zone 9 contains the lift and swing spans, which include movable bearings and operational joints specifically designed to accommodate larger structural movements. The displacement behavior of PS points in this region is therefore expected to differ from that of the adjacent fixed spans. Moderate anomaly concentrations observed near the terminal zones (Z1 and Z12) are also consistent with the bearing and restraint behavior commonly observed

## 5.7. CONCLUSION

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near bridge abutments. In contrast, the relatively low anomaly density observed over the regular simply-supported spans suggests a more uniform structural response along the main deck.

It is important to emphasize that an anomaly in this study does not necessarily indicate structural damage or imminent failure. Instead, an anomalous PS point represents a displacement time series that deviates from the dominant temporal behavior observed across the bridge. Consequently, anomaly clusters should be interpreted as regions exhibiting a different structural response relative to the bridge-wide trend, rather than as direct evidence of deterioration. The proposed framework is therefore intended as a screening and prioritization tool to help identify regions that may warrant closer inspection or additional monitoring.

## 5.7 CONCLUSION

This study presented a spatially structured and interpretable framework for PS-InSAR-based anomaly detection in bridge monitoring, demonstrated on the Victoria Bridge in Montreal using Sentinel-1, RADARSAT-2 and RCM datasets spanning multiple time periods and both ascending and descending acquisition geometries. The proposed framework combines feature-based anomaly detection, bootstrap stability filtering, SHAP-based interpretation, spatial consistency refinement, LOS-based bridge-axis projection and zone-level anomaly density analysis into a unified workflow capable of transforming point-wise PS displacement irregularities into spatially organized representations of structural response. The results showed that spatial filtering is an essential step for improving the interpretability of PS-InSAR anomaly detection results. Without spatial refinement, many detected anomalies appear as isolated points that lack meaningful spatial continuity. The neighborhood-based consistency filter substantially reduced the number of retained anomalies across all datasets, particularly for Sentinel-1, where the lower PS density increases the likelihood of isolated detections. The anomaly patterns were also found to be spatially non-uniform along the bridge. The most consistent anomaly concentrations were observed around Zones 7–9, corresponding to the longest through-truss span and the lift/swing spans, both of which differ structurally from the surrounding regular deck spans. These regions repeatedly

### 5.7. CONCLUSION

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exhibited elevated anomaly density across multiple datasets, suggesting that the framework is capturing physically meaningful variations in structural response rather than random measurement noises. The cross-satellite comparison revealed that agreement between datasets is more consistent at the level of dominant anomaly-prone regions than in the detailed ranking of bridge zones. In particular, the descending datasets showed stronger agreement around Zones 7–8, whereas the ascending datasets exhibited weaker spatial consistency and more sensor-dependent anomaly distributions. An additional observation was the directional dependence observed in the Sentinel-1 datasets, where the dominant anomaly concentrations in the descending passes were primarily located toward the eastern portion of the bridge, while the ascending passes showed elevated anomaly density predominantly on the western side. This behavior highlights the influence of LOS geometry on anomaly interpretation and demonstrates that acquisition geometry can significantly affect the spatial distribution of detected anomalies. It is important to emphasize that an anomaly in this context does not necessarily indicate structural damage or imminent failure. Rather, anomalous PS points represent displacement behaviors that deviate from the dominant structural trend observed across the bridge. Consequently, the proposed framework should be interpreted primarily as a spatial screening and prioritization tool capable of identifying regions that may warrant closer inspection or additional monitoring. Overall, the results demonstrate that spatially structured PS-InSAR anomaly detection, combined with physically informed spatial analysis and multi-satellite comparison, provides a valuable complement to conventional bridge monitoring approaches. The proposed framework is readily transferable to other long-span steel bridges where PS-InSAR observations are available and can be adapted to different structural configurations, sensor combinations and monitoring objectives.



# CHAPTER 6

## SYNTHESIS, INTEGRATION AND GENERAL DISCUSSION OF RESULTS

### 6.1 INTRODUCTION

This thesis set out to advance remote sensing of bridge infrastructure by addressing two distinct but fundamentally interconnected challenges: the detection of structural damage in bridge components using deep learning techniques trained on numerically simulated structural response data, and the large-scale remote monitoring of bridge displacements using satellite-based PS-InSAR interferometric measurements integrated with machine learning for anomaly detection. Although these two approaches operate at different sensing scales and rely on entirely different data sources, they share a common underlying purpose, to extract meaningful, reliable, and interpretable information about structural condition from complex time-series signals. The preceding chapters have addressed each of these challenges through dedicated methodological investigations. The present chapter brings these threads together in a unified synthesis, examining how the individual contributions complement and reinforce one another, and what their collective implications are for the field of structural health monitoring.

The organization of this research was deliberately structured to progress from fundamental methodological groundwork toward increasingly complex, real-world applications. Chapter 3 established the viability of advanced deep learning architectures, Long Short-Term Memory (LSTM) networks, Multivariate Time-Series Transformers (MTT), and LSTM-based autoencoders, for classifying structural damage states in a controlled simulation environment. Chapter 4 then converted the data-driven anomaly detection concept into the domain of satellite remote sensing, developing an integrated PS-InSAR and machine learning framework for bridge displacement monitoring validated on the Victoria Bridge in Montreal. Chapter 5 extended and deepened this

## 6.2. SUMMARY OF MAIN FINDINGS

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satellite-based monitoring work through a spatially structured, multi-satellite analysis that introduced zone-based anomaly density metrics and cross-satellite consistency evaluation. Together, these three studies constitute a coherent research program that spans a wide spectrum from FE models of individual structural components to large-scale real-world infrastructure, and from local point data to spaceborne radar observations.

The purpose of this integrative discussion is threefold. First, it synthesizes the principal findings from each study, drawing out the key lessons learned about the behavior of deep learning models and anomaly detection algorithms in structural monitoring context. Second, it reflects critically on the limitations of the work and discusses the broader implications of the findings for the practice of infrastructure monitoring and the future trajectory of data-driven SHM research.

## 6.2 SUMMARY OF MAIN FINDINGS

### 6.2.1 DEEP LEARNING METHODS FOR STRUCTURAL DAMAGE DETECTION (FROM CHAPTER 3)

The first research contribution of this thesis examined the capability of three advanced deep learning architectures to detect and localize structural damage in a cantilever steel I-beam, using simulated acceleration time-history data generated through a finite element model in Abaqus. A total of 1,443 structural response samples were generated, representing both undamaged states and a range of realistic damage configurations, bottom flange reductions, web openings, and combined damage at four spatial locations along the beam length. These scenarios were deliberately designed to reflect corrosion patterns documented in field surveys of steel bridge girders, ensuring that the simulation framework maintained a meaningful connection to real-world structural degradation.

The three architectures evaluated, LSTM, supervised and unsupervised Multivariate Time-Series Transformers, and LSTM-based autoencoders, each brought distinct strengths to the structural damage classification problem. The LSTM architecture proved to be a reliable and consistent

## 6.2. SUMMARY OF MAIN FINDINGS

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performer, achieving near-perfect classification accuracy for the binary discrimination between damaged and undamaged beams (Damage Class 1) across all monitored points and configurations, including sparse inputs with as few as four measurement points. This result is noteworthy because it demonstrates that even relatively compact LSTM models can reliably detect the presence of structural damage without requiring dense sensor arrays. The LSTM architecture performed particularly well for damage located near the supported end of the beam (Quarter 4, Class 5), with F1-scores approaching unity under the best configurations. However, classification performance degraded for damage near the unsupported free end of the cantilever beam (Quarter 1, Class 2), especially when fewer sensor points were used. This spatial dependence reflects the well-known challenge in vibration-based SHM of localizing damage in regions where structural response sensitivity is inherently lower.

The Multivariate Time-Series Transformer models demonstrated a compelling advantage over LSTM in terms of convergence efficiency and damage localization performance. Both the supervised and unsupervised variants achieved comparable or superior average F1-scores relative to LSTM, and the unsupervised MTT, which underwent a masking-based pre-training phase, outperformed its supervised counterpart by approximately 2.5% on average across all classes, with particular robustness under reduced monitored locations. This result has important practical significance: the unsupervised pre-training paradigm allows the model to develop rich representations of the structural response signal without requiring labeled damage examples, which are inherently scarce in real infrastructure monitoring scenarios. The MTT achieved its best performance with six monitored points as input, and the optimal model comprised three encoder blocks with eight multi-head attention heads, a feedforward dimension of 256, and an embedding dimension of 128. The AUC value of 0.85 for the unsupervised MTT in the multiclass ROC analysis confirmed its superior discriminative capacity across all damage classes.

The LSTM-based autoencoder offered a fundamentally different approach to the classification problem, operating as an unsupervised anomaly detector that learned the reconstruction of undamaged structural responses and flagged departures from this learned baseline as anomalies. Because undamaged samples were substantially less numerous than damaged ones in the dataset, the training data was augmented by generating noisy variants of the undamaged class, expanding

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the effective undamaged dataset from 292 to 1,460 samples. The autoencoder demonstrated a reliable separation between the reconstruction error distributions for undamaged and damaged inputs, with the anomaly threshold defined as the median reconstruction loss plus three times its median absolute deviation (MAD). While the autoencoder was highly effective at identifying severe and unambiguous damage conditions, its performance on minor or subtle damage was inherently constrained by the binary nature of the anomaly threshold, a challenge common to reconstruction-based anomaly detection approaches. Critically, the autoencoder does not provide spatial localization of damage in the way that the LSTM and transformer models do, making it better suited as a damage presence detector than as a damage localizer.

A key cross-cutting finding from Chapter 3 is the consistent importance of the density of the monitored points on model performance. Across all three DL architectures, reducing the number of input data points from nine to four generally degraded classification performance, particularly for the more challenging spatial damage classes. This reflects a fundamental information-theoretic constraint: as measurement coverage decreases, the structural response signals become less informative about the location and character of damage and models must work harder to discriminate between superficially similar response patterns. At the same time, the fact that all three architectures maintained useful performance even with only four monitored points is encouraging from a practical standpoint, since installing dense permanent instrumentation is rarely feasible on aging bridge infrastructure. The results collectively suggest that a carefully designed sparse sensor network, combined with appropriate deep learning architectures, can still support meaningful structural condition assessment.

### 6.2.2 PS-IN SAR-BASED DISPLACEMENT MONITORING WITH EXPLAINABLE ANOMALY DETECTION (FROM CHAPTER 4)

Before presenting the PS-InSAR findings, it is important to explain the transition in methodology between Chapter 3 and Chapters 4 and 5, as the two research components rely on fundamentally different machine learning approaches. In Chapter 3, supervised deep learning models, LSTM, MTT, and LSTM-based autoencoder, were appropriate because the training data was generated

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through controlled finite element simulations, where damage states were precisely known and labeled. This allowed the models to learn discriminative features directly from pairs of damaged and undamaged structural responses. In the satellite monitoring context of Chapters 4 and 5, however, no such labeled data exists. The Victoria Bridge has not experienced any documented structural failure during the monitoring period, and no ground-truth record of damage states is available for the PS displacement time series. Supervised learning is therefore not applicable. The Isolation Forest algorithm was selected precisely because it operates in a fully unsupervised manner, requiring only the normal operational data to identify statistical outliers, without any prior knowledge of what a damaged or anomalous state looks like. This shift from supervised deep learning on simulated data to unsupervised anomaly detection on real satellite data reflects a deliberate and necessary adaptation to the fundamentally different data availability conditions that characterize laboratory-scale simulation versus real-world satellite-based structural monitoring.

The second major contribution of this thesis shifted the analytical focus from local vibration data to spatially distributed, long-term displacement time series derived from satellite radar observations. The Victoria Bridge in Montreal, a 160-year-old through-truss railway and roadway bridge spanning the St. Lawrence River, served as the case study for this investigation. Sentinel-1 Synthetic Aperture Radar data from both ascending and descending orbital passes were processed over a five-year period from January 2020 to December 2024, using the SNAP and StaMPS software workflow to generate Persistent Scatterer (PS) displacement time series over the bridge. Before the final processing, low-coherence interferograms, particularly those acquired during winter months when snow and ice cover the bridge deck, were removed to improve the reliability and temporal smoothness of the resulting displacement histories.

The PS-InSAR analysis yielded coherent displacement time series for hundreds of persistent scatterer points distributed along the bridge deck. The raw time series exhibited clear seasonal cyclicity driven by thermal expansion and contraction, an expected and dominant behavior for such a large steel bridge structure exposed to Montreal's substantial annual temperature range. A thermal sensitivity analysis was carried out by performing linear regression between the detrended PS displacement series and synchronous temperature records, with the regression slope representing the displacement response per degree Celsius for each scatterer (i.e., a unit thermal

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displacement). The results revealed a spatially coherent and physically consistent pattern: ascending and descending passes showed complementary, mirror-image thermal sensitivity profiles along the bridge axis, consistent with the support conditions of the Victoria Bridge, in which each span is fixed at its pin end and free to expand thermally toward its roller end. Since the pin-roller orientation reverses at the middle of the bridge, with spans on the west half expanding eastward and spans on the east half expanding westward, the overall thermal displacement pattern is symmetric about the bridge midpoint, producing the mirror-image sensitivity profiles observed in the ascending and descending satellite passes.

The anomaly detection framework was built on a feature extraction step that transformed each PS displacement time series into a nine-dimensional feature vector, capturing long-term velocity, temporal variability (median absolute deviation, first-difference standard deviation), autocorrelation, trend and seasonal strength, thermal sensitivity, and distributional shape (skewness and kurtosis). These features were selected to be both statistically diverse and physically interpretable, avoiding redundancy while covering the principal modes of displacement behavior relevant to bridge monitoring. The Isolation Forest algorithm was then trained separately on the ascending and descending feature matrices, assigning an anomaly score to each PS point based on the ease with which it could be isolated from the majority of scatterers. The model was configured with 300 trees, a subsample size of 256 observations per tree, and automatic contamination was selected to allow the algorithm to infer the anomaly fraction from the data distribution.

The Isolation Forest results revealed physically meaningful spatial patterns. Anomalous PS points were preferentially concentrated near the roller ends of the bridge spans and at the expansion joints of the bridge deck, which is physically consistent with the support configuration of the Victoria Bridge. These are precisely the locations where thermal displacement is maximum, unconstrained by the pin supports, and where cumulative differential movement between adjacent spans is largest. The consistency of anomaly detections across independent ascending and descending model runs reinforced the reliability of these identifications. A bootstrap stability analysis with 30 resampling iterations further filtered the anomaly list to retain only those PS points persistently flagged across multiple runs, distinguishing genuinely unusual scatterers from spurious noise-driven detections.

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The integration of SHAP (SHapley Additive exPlanations) interpretability provided a crucial layer of transparency to the anomaly detection results. Rather than simply identifying which PS points were anomalous, SHAP analysis quantified exactly which features drove each classification decision, enabling a direct link between statistical outlier behavior and physical structural mechanisms. For the ascending pass (acquired in the late afternoon around 6 PM), short-term variability features, particularly the first-difference standard deviation and MAD, dominated anomaly attribution, consistent with the heightened thermal and atmospheric variability experienced by the bridge during afternoon hours (e.g., lag between measured ambient temperature and actual bridge temperature). For the descending pass (acquired in the early morning near thermal equilibrium at around 6 AM), long-term drift features, trend strength and velocity, were the primary drivers of anomaly classification. These acquisition-time-dependent differences in feature importance were physically coherent and demonstrated that the model was responding to genuine structural and environmental signals rather than random signal noise.

Critically, this study highlighted that the detected anomalies represent statistical deviations from the dominant displacement pattern, rather than indicators of structural abnormal response with imminent danger to the integrity of the bridge. The displacement magnitudes involved were entirely consistent with normal thermal and environmental behavior for a steel bridge of this type and age. This distinction, between statistical anomaly and structural performance, is fundamental to the responsible application of satellite-based monitoring and was consistently maintained throughout the interpretation of results in Chapter 4.

### 6.2.3 MULTI-SATELLITE SPATIALLY STRUCTURED FRAMEWORK FOR ANOMALY CONSISTENCY (FROM CHAPTER 5)

The third research contribution extended the PS-InSAR analysis of the Victoria Bridge to a multi-satellite context, incorporating data from Sentinel-1, RADARSAT-2 and the RADARSAT Constellation Mission across both ascending and descending acquisition geometries and two time periods (2016-2018 and 2022-2024). A fundamental challenge in this context is that the three satellite systems are independent remote sensing platforms monitoring the same bridge

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structure but with substantially different characteristics. Sentinel-1 provides a larger number of scenes with moderate spatial resolution (5 x 20 m), resulting in comparatively sparse PS distributions over the bridge (1,741 ascending and 797 descending PS points). In contrast, RADARSAT-2 and RCM offer significantly higher spatial resolution (3 x 1 m), yielding much denser PS coverage: RADARSAT-2 produced 15,472 ascending and 34,642 descending PS points, while RCM produced 8,697 ascending and 12,647 descending PS points. These differences in PS points density, incidence angle, revisit schedule, and acquisition geometry mean that the displacement measured by different satellites cannot always be directly compared, leading to potential inconsistencies in anomaly detection results across datasets. For all satellites, PS points were more densely concentrated on structural elements such as trusses and deck components, with sparser and less reliable coverage near the ends of the bridge where the surrounding water body reduces interferometric coherence.

The central methodological innovation of Chapter 5 was the introduction of a spatially structured analysis framework that replaced point-wise anomaly comparisons with a zone-based representation. PS points were projected onto the longitudinal axis of the bridge using a line-of-sight (LOS) consistent geometric transformation, ensuring that the projection remained consistent with the radar acquisition geometry of each satellite. The bridge was then divided into 12 variable-length zones approximately aligned with every two structural spans, enabling spatial aggregation of anomaly information at the segment level rather than at individual PS points. A relative anomaly density metric was defined by normalizing the zone-level anomaly proportion against the global dataset anomaly rate, enabling valid cross-satellite comparison despite differences in overall PS availability and anomaly thresholds across datasets.

A spatial filtering procedure was introduced prior to the zone-based analysis as a novel step to remove unverified isolated anomalous PS points that lacked sufficient spatial support from neighboring anomalous scatterers. This step substantially reduced the number of retained anomalous PS points across all datasets, with the reduction ratio varying considerably by satellite and pass geometry. For Sentinel-1, spatial filtering reduced the anomaly count from 65-87 points to only 12-16 spatially coherent candidates (retention ratio of approximately 0.18 across passes), reflecting its lower PS density and greater susceptibility to isolated detections. For RCM, the



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reduction was less severe, retaining 245-599 anomalous points from initial counts of 678-1,063 (retention ratio of 0.36-0.56). RADARSAT-2 retained 187-474 anomalous points from initial counts of 634-1,488 (retention ratio of 0.29-0.32). These results confirm that spatial filtering does not affect all datasets uniformly: its impact is strongest where PS density is lowest and isolated detections are most likely. It is important to note that the filtered anomaly labels represent statistically and spatially coherent deviations in PS displacement behavior, not assessments of structural damage or safety, since no independent structural condition data were available to support such conclusions.

The relative anomaly density profiles revealed that anomalies were not uniformly distributed along the bridge. For the descending datasets, both Sentinel-1 and RADARSAT-2 exhibited a pronounced anomaly concentration around Zones 7-8, corresponding approximately to bridge spans 13-16 near the center of the structure. This spatial pattern was the most consistent finding across the descending datasets and represents the most reliable anomaly-prone region identified by the framework. The RCM descending dataset, despite its high PS density, showed a comparatively flatter anomaly profile with weaker spatial concentration, suggesting that higher PS density does not automatically translate into stronger spatial agreement. For the ascending datasets, consistency was substantially lower: both Sentinel-1 ascending datasets showed elevated anomaly density around Zone 2, while RADARSAT-2 ascending reached its dominant peak near Zone 9, and RCM ascending again showed limited spatial concentration. A clear directional dependence was observed specifically in the Sentinel-1 datasets, where descending passes concentrated anomalies toward the eastern portion of the bridge while ascending passes concentrated them on the western side, consistent with the different displacement components captured by opposite viewing geometries. Overall, among the three satellite systems, RADARSAT-2 produced the sharpest and most localized anomaly peaks, attributable to its denser PS coverage and higher spatial resolution, while Sentinel-1 produced broader and smoother profiles. RCM, despite its high resolution, showed the flattest profiles across both passes.

Cross-satellite agreement was quantified using two complementary metrics. The Top-7 zone overlap analysis showed that several dataset pairs identified a common subset of highly anomalous zones, with overlap values ranging from 0.43 to 0.86. The strongest agreement was observed

### 6.3. *METHODOLOGICAL ADVANCES AND CONTRIBUTIONS TO PRACTICE*

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between datasets sharing similar acquisition geometry or time period: for example, Sentinel-1 ascending and Sentinel-1 2016 ascending achieved perfect overlap (1.0), and RCM descending and Sentinel-1 2016 descending also reached 0.86. However, agreement between datasets from different satellites and different acquisition geometries was generally more moderate, confirming that full cross-satellite consistency should not be expected. The Spearman rank correlation analysis provided a more demanding test of agreement, comparing the full ordering of zones by anomaly intensity rather than only the top subset. Correlations ranged widely, from moderately positive values (e.g., RCM descending and Sentinel-1 ascending at 0.74, and Sentinel-1 2016 descending and Sentinel-1 descending at 0.52) to negative values in several pairs, indicating that fine-scale zone ranking is sensitive to satellite-specific factors including spatial resolution, PS density, and acquisition geometry. This distinction has practical importance: multi-satellite PS-InSAR monitoring is more reliable for identifying which broad regions of the bridge are anomaly-prone than for establishing precise numerical rankings of anomaly intensity across zones. Fine-scale prioritization of inspection targets based on a single satellite anomaly ranking should therefore be interpreted with caution.

## 6.3 METHODOLOGICAL ADVANCES AND CONTRIBUTIONS TO PRACTICE

### 6.3.1 ADVANCING DEEP LEARNING BENCHMARKS FOR SHM

The comparative evaluation of LSTM, MTT and LSTM-autoencoder architectures in Chapter 3 represents one of the first systematic benchmark studies to assess Transformer-based models specifically within the context of structural damage detection using acceleration response data. Prior to this work, the application of Transformer architectures in SHM had been limited and the existing comparative literature was scattered across different structural systems, damage types, sensor configurations and evaluation methodologies, making cross-study comparisons unreliable. By implementing all three architectures under a consistent experimental protocol,

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identical dataset, identical train/test split, identical hyperparameter search strategy, and identical evaluation metrics, this thesis provides a rigorous empirical foundation for assessing the relative merits of these approaches.

The finding that the unsupervised Multivariate Time-Series Transformer achieved the highest overall performance, while also being the most sample-efficient under reduced number of monitored points, has important implications for SHM practice. It suggests that the pre-training paradigm, leveraging unlabeled normal operational data to develop rich temporal representations before fine-tuning for downstream tasks, may offer a promising direction for structural monitoring applications where labeled damage data is inherently scarce. The masking-based pre-training strategy employed in the unsupervised MTT bears structural similarity to recent advances in self-supervised learning in natural language processing and computer vision, and the positive results obtained here suggest that analogous transfer learning strategies could be fruitfully explored in SHM contexts.

The finite element simulation framework developed for data generation also constitutes a methodological contribution of its own. By automating the generation of structural response data across a large combinatorial space of damage types, locations, and severities using Python scripting within the Abaqus environment, the study created a replicable template for efficient, large-scale damage scenario generation that could be readily extended to more complex structural systems including orthotropic steel decks, box girders, and full bridge models. The use of corrosion patterns documented in field surveys of real bridge girders to define the damage scenarios ensured that the simulation results maintained a meaningful connection to practical structural degradation mechanisms, enhancing the transferability of the conclusions.

#### 6.3.2 ESTABLISHING AN INTEGRATED PS-IN SAR AND MACHINE LEARNING PIPELINE

The integrated framework developed in Chapter 4 represents a significant methodological advance over existing PS-InSAR-based bridge monitoring studies, which have predominantly focused on

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displacement velocity mapping and visual interpretation of temporal trends without systematic anomaly detection or interpretability mechanisms. By coupling the established PS-InSAR processing pipeline with automated feature extraction, Isolation Forest anomaly detection, bootstrap stability filtering, and SHAP-based attribution, the framework provides a complete, automated pathway from raw satellite data to physically interpretable structural monitoring outputs.

Several specific design choices merit discussion as methodological contributions. The use of bootstrap stability analysis, running 30 independent Isolation Forest models on random 80% subsamples of the data and retaining only PS points flagged as anomalous in more than 70% of runs, substantially improved the reliability of anomaly identifications compared to single-run model evaluations. This approach addresses the inherent stochasticity of the Isolation Forest algorithm and ensures that reported anomalies reflect consistent patterns in the data rather than chance outcomes of a single model run. The stability filtering proved particularly important for distinguishing persistent, structurally meaningful anomalies from transient, noise-driven detections.

The use of SHAP values for both global feature importance ranking and local, instance-level explanation represents a meaningful enhancement to the interpretability of PS-InSAR-based monitoring results. Previous applications of machine learning to PS-InSAR data have rarely incorporated explainability mechanisms, treating the anomaly classification as a black box. By providing feature-level attribution for each PS point, the framework enables structural engineers to understand why a particular location was flagged, connecting the statistical classification to physically interpretable displacement characteristics. This interpretability layer is essential for building engineering trust in the outputs of data-driven monitoring systems and for supporting informed decision-making about inspection priorities.

#### 6.3.3 SPATIAL STRUCTURING AND CROSS-SATELLITE VALIDATION

The spatial analysis framework introduced in Chapter 5 addresses a fundamental gap in the existing PS-InSAR bridge monitoring literature: the lack of systematic methods for aggregating

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and comparing point-wise anomaly detection results across datasets with different PS distributions and satellite characteristics. The bridge-axis projection approach, which maps PS points onto the longitudinal axis of the bridge using a line-of-sight consistent geometric transformation, creates a physically meaningful one-dimensional representation that directly corresponds to the structural layout of the bridge. Combined with the span-based zone definitions, this framework enables the identification of structurally meaningful anomaly patterns at the level of bridge segments rather than individual scatterer points.

The introduction of the relative anomaly density metric, normalizing zone-level anomaly proportions by the global dataset anomaly rate, is a conceptually simple but practically important innovation that enables valid comparison across datasets with very different overall anomaly fractions. Without this normalization, direct comparison of absolute anomaly counts between a sparse Sentinel-1 dataset and a denser RADARSAT dataset would be misleading. With normalization, both datasets can be expressed in terms of how much more or less anomalous each zone is relative to the typical level for that satellite, enabling genuine spatial comparisons.

The cross-satellite validation using Top-K overlap and Spearman rank correlation provided an honest and nuanced picture of inter-satellite agreement that avoids both overclaiming and underclaiming. The finding that spatial pattern agreement is stronger at the coarse level of zone identification than at the fine level of zone ranking is practically actionable: it indicates that multi-satellite PS-InSAR analysis is most trustworthy for identifying broadly which bridge regions warrant attention, rather than for establishing precise rankings of anomaly severity.

## 6.4 CRITICAL REFLECTIONS ON RESEARCH LIMITATIONS

### 6.4.1 LIMITATIONS OF THE DEEP LEARNING DAMAGE DETECTION STUDY

The deep learning study, while methodologically rigorous within its own scope, is subject to several limitations. Most fundamentally, the entire analysis was conducted on simulation data from a single, relatively simple structural component: a 2-meter cantilever I-beam under a

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specific loading configuration. While finite element modeling enables precise control over damage scenarios and data generation at scale, the resulting dataset represents an idealized structural response that differs from real-world monitoring data in several important ways. Real accelerometers are subject to complex noise spectra, sensor drift, temperature effects on transducer sensitivity and electromagnetic interference. Traffic-induced vibrations are stochastic and non-stationary. The dynamic loading of a real bridge is far more complex than the linear pressure ramp applied in the simulation. These differences mean that the performance metrics reported in Chapter 3, while internally valid, cannot be directly extrapolated to predict model performance on field data from real bridges without further experimental validation.

A second limitation is the single noise level employed in the study. Gaussian noise with a fixed standard deviation was added to all samples uniformly, but the effect of varying noise intensity on model performance was not systematically explored. In real monitoring scenarios, signal-to-noise ratios vary substantially depending on sensor type, installation quality, structural damping, and ambient vibration levels. Understanding how model performance degrades as noise increases is critical for establishing the practical operating envelope of each deep learning architecture. Additionally, the damage scenarios were limited to three types of cross-sectional modification applied at four spatial locations, omitting more complex patterns such as progressive fatigue cracking, multiple simultaneous damage sites, or partial loss of boundary conditions. Finally, the autoencoder's inability to provide spatial localization information is a notable functional limitation compared to the LSTM and transformer approaches, and deployment scenarios requiring damage location information would need to complement it with one of the supervised classification architectures.

##### 6.4.2 LIMITATIONS OF THE PS-IN SAR MONITORING STUDY

The PS-InSAR-based monitoring study is subject to a different but equally important set of limitations. The most fundamental is the absence of validation with field data of the anomaly detection results. Unlike the simulation study, where damage states were precisely known by construction, the Victoria Bridge monitoring study did not have access to independent structural

#### 6.4. *CRITICAL REFLECTIONS ON RESEARCH LIMITATIONS*

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condition assessments that could validate whether the flagged PS points correspond to genuine structural issues or measurement artifacts. The consistency of anomaly detections across independent ascending and descending passes and across multiple satellite systems provides indirect evidence that at least some of the detected anomalies reflect genuine structural or environmental signals rather than random noise. However, without concomitant field inspection data, it remains impossible to definitively distinguish between a genuine structural irregularity, a localized measurement noise, or a physically real but structurally unimportant effect such as differential thermal expansion between structural elements with different sun exposure conditions.

The spatial resolution limitation of Sentinel-1 (approximately  $5 \times 20$  m) means that individual PS points may integrate the radar response of multiple structural elements within a single resolution cell, making it difficult to attribute anomalous displacement to a specific structural component. The higher resolution of RADARSAT-2 and RCM (approximately  $3 \times 1$  m) partially addresses this issue, but even at this resolution the attribution of displacement to specific structural elements requires careful interpretation. The coherence constraints of PS-InSAR impose a further limitation on spatial coverage, as the bridge is surrounded by water, a zero coherence surface in SAR imagery, meaning that edge regions of the bridge deck often have limited PS availability, leading to uneven spatial coverage that can bias anomaly detection results toward zones with better PS density.

Additionally, the PS-InSAR displacement measurements are inherently projected along the satellite line-of-sight direction and converting them to physically interpretable vertical or horizontal displacements requires either multi-look decomposition using ascending and descending measurements or assumptions about the dominant deformation direction. While the thermal sensitivity analysis and physical interpretation of anomaly patterns were conducted in consistent LOS terms, the direct comparison of LOS measurements between satellites with different incidence angles and acquisition geometries introduces additional complexity that limits the precision of cross-satellite comparisons.

# CHAPTER 7

## CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE WORK

### 7.1 CONCLUSIONS

This thesis advanced remote sensing structural health monitoring of bridge infrastructure through two complementary research directions: deep learning-based structural damage detection using numerically simulated response data and satellite PS-InSAR coupled with explainable machine learning for long-term displacement monitoring. Together, the technical studies addressed persistent gaps in the SHM research, the lack of systematic benchmarking of advanced time-series architectures under controlled damage conditions, the integration of explainable anomaly detection with PS-InSAR bridge analysis, and the absence of a unified cross-satellite consistency framework for bridge-specific anomaly detection.

The comparative deep learning study demonstrated that all three evaluated architectures, LSTM, Multivariate Time-Series Transformer and LSTM-based autoencoder, can reliably detect the binary presence of structural damage in a cantilever steel I-beam even with as few as four measurement points. Damage localization was more challenging, with performance degrading consistently as density of monitored points decreased and as damage approached the free end of the cantilever steel beam, where structural response sensitivity is inherently lower. The unsupervised MTT achieved the strongest overall performance, with an average F1-score of 0.86 using six monitored points and an AUC of 0.85 in the multiclass ROC analysis, outperforming its supervised counterpart by approximately 2.5 % on average. The advantage of the unsupervised pre-training paradigm, leveraging unlabeled data to build rich temporal representations before classification, is particularly valuable in SHM contexts where labeled damage examples are inherently scarce. The LSTM-based autoencoder proved reliable as an unsupervised damage



## 7.1. CONCLUSIONS

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presence detector but offers no spatial localization, making it most appropriate as a complement to supervised classification approaches rather than a standalone solution.

The integrated PS-InSAR and machine learning framework, employing five years of Sentinel-1 data for the Victoria Bridge in Montreal, produced physically coherent and interpretable displacement monitoring results. Thermal sensitivity analysis confirmed that the dominant deformation mechanism is thermally driven, with ascending and descending passes producing complementary sensitivity profiles consistent with the bridge's simply supported spans' structural configuration. The Isolation Forest anomaly detection framework, operating on a nine-feature representation of each PS displacement time series, identified anomalous scatterers concentrated near the roller ends of the spans and at the expansion joints, zones where thermal displacement is maximum and cumulative differential movement between adjacent spans is largest. Bootstrap stability filtering across 30 resampled model runs proved essential for separating persistent, physically meaningful anomalies from noise-driven detections. SHAP analysis confirmed that feature importance differed systematically between ascending and descending passes in a physically explicable manner, demonstrating that the model was responding to genuine structural and environmental signals. All detected anomalies were statistically significant but entirely consistent in magnitude with normal thermal and environmental behavior for a steel bridge of this age and type.

The multi-satellite remote sensing extension of Victoria Bridge, incorporating datasets from Sentinel-1, RADARSAT-2 and RADARSAT Constellation Mission across ascending and descending geometries and two time periods, demonstrated that spatial filtering based on neighborhood consistency markedly improved anomaly interpretability across all datasets. Bridge-axis projection and segregation into twelve span-aligned zones, combined with relative anomaly density normalization, enabled meaningful cross-satellite comparison for the first time in a bridge monitoring context. Relative anomaly density profiles were consistently elevated in the mid-span zones across multiple datasets, confirming a genuine spatial signal independent of satellite characteristics. Cross-satellite agreement was meaningful at the coarse level of zone identification but limited at the fine level of zone ranking, leading to the practical conclusion that multi-satellite PS-InSAR monitoring reliably identifies which bridge regions warrant attention but should not be expected to produce consistent fine-scale rankings of anomaly intensity. From an engineering

## 7.2. *RECOMMENDATIONS FOR FUTURE WORK*

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perspective, these results suggest that multi-satellite PS-InSAR should be used as a complementary decision-support tool rather than as a replacement for conventional bridge inspections or instrumented structural health monitoring systems. Consistent anomaly patterns identified across multiple satellite missions can help engineers prioritize bridge regions for detailed inspection and maintenance, while the higher spatial resolution offered by RADARSAT-2 and the RADARSAT Constellation Mission provides additional confidence for localized assessment. This integrated approach has the potential to improve inspection planning, optimize resource allocation, and support more informed bridge management decisions.

## 7.2 RECOMMENDATIONS FOR FUTURE WORK

The most immediate research priority is the extension of the validated deep learning architectures to field-recorded structural response data from real bridge structures. The envisioned follow-up of this research program targets orthotropic steel decks with artificially induced damage, providing a higher-fidelity test environment while retaining experimental control. Transfer learning strategies, pre-training on simulation data and fine-tuning on small volumes of real monitoring signals, should be explored to reduce the labeled data requirements for field deployment. Noise robustness evaluation should be extended to varying noise levels, noise types and sensor dropout configurations to define the practical operating envelope of each architecture under realistic monitoring conditions.

The success of the unsupervised MTT pre-training approach motivates further development of SHM-specific self-supervised learning objectives, such as predicting structural response at unobserved sensor locations or reconstructing signals under specified loading perturbations. Physics-informed neural networks that embed structural mechanics constraints directly into the learning architecture represent a complementary direction that could improve generalization across structural systems while reducing training data demands.

For the PS-InSAR component, ground-truth validation is the most critical unresolved need. Concurrent satellite monitoring and permanent sensor deployment on an instrumented bridge

## *7.2. RECOMMENDATIONS FOR FUTURE WORK*

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would enable direct comparison of satellite-detected anomalies with measured structural response changes. Correlating anomaly onset with maintenance logs, inspection records, and traffic load histories would provide causal context currently absent from the analysis. Ground-based technologies such as terrestrial radar interferometry and LiDAR could supply high-accuracy point-level displacement references to validate the PS-InSAR time series directly.

Extending the framework to cable-stayed, suspension and continuous-span bridge types would test the generality of the feature engineering and spatial analysis methodology, and may require adaptations for the qualitatively different deformation mechanisms these systems exhibit.

Finally, the public release of the simulation dataset developed in this thesis, together with open-source implementations of the analytical frameworks, would enable rigorous cross-study benchmarking and support the reproducibility required for responsible transfer of these methods into engineering practice. The development of a publicly available PS-InSAR bridge monitoring benchmark dataset with coincident structural ground truth remains an important outstanding need for the broader research community.

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# APPENDICES

# APPENDIX A

## PS-IN SAR PROCESSING WORKFLOW

### A.1 LOADING PERSISTENT SCATTERER (PS) CANDIDATES

The first step in the StaMPS processing workflow involves loading the interferometric dataset, which was prepared and exported from SNAP2StaMPS.

In this step, all interferometric data, including wrapped phase, amplitude values, and metadata from multiple Sentinel-1 acquisitions, are imported into StaMPS. At this stage, no filtering or stability assessment is applied. Instead, the software retrieves all pixels from the interferograms, maintaining a complete dataset to prevent premature exclusion of potentially useful scatterers.

One of the crucial tasks in this step is ensuring that the interferogram stack is correctly referenced to the selected master image. Since PS-InSAR depends on phase consistency across time-series data, any misalignment at this stage could introduce distortions that would propagate through subsequent processing steps. Additionally, StaMPS stores the wrapped phase matrix, which will be used in later steps for Persistent Scatterer selection, phase unwrapping, and velocity estimation.

At this point, the dataset is fully loaded into StaMPS, but it remains unfiltered. The next step involves estimating phase stability and selecting Persistent Scatterers based on their temporal behavior. This initiates a more refined selection process, where unreliable pixels are progressively filtered out, leading to a more accurate and reliable assessment of displacement trends on the bridge.

### A.2 TEMPORAL COHERENCE ESTIMATION AND INITIAL PS SELECTION

After importing the interferometric dataset and initializing Persistent Scatterer candidates, the next step in StaMPS processing is to evaluate temporal coherence, essentially measuring how consistently a scatterer maintains its phase stability over time. This step is crucial because not all points in the dataset remain stable across multiple SAR acquisitions. Some scatterers may be affected by noise, atmospheric disturbances, or surface changes, making them unreliable for

## *A.2. TEMPORAL COHERENCE ESTIMATION AND INITIAL PS SELECTION*

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tracking long-term displacement. To identify the most stable scatterers, StaMPS calculates gamma values for each PS candidate. The higher the gamma value, the more reliable the scatterer is for long-term monitoring. This evaluation is performed iteratively, refining coherence estimates with each cycle to ensure that only the most stable scatterers are retained. The process effectively filters out pixels with inconsistent phase responses, improving the accuracy of the final displacement results.

Several key parameters influence this step:

- **Gamma Threshold:** Defines the minimum level of phase stability required for a point to be classified as a PS. A high value of gamma ensures that only stable scatterers are selected, but setting it too high may remove useful points. To ensure the balance between data coverage and precision, the gamma change convergence threshold for this study was set to 0.005, meaning that StaMPS stops iterating when the improvement in gamma values is minimal. Additionally, the maximum number of gamma estimation iterations was set to 10, preventing unnecessary computation while refining the selection process.
- **Maximum Uncorrelated DEM Error:** Helps filter out scatterers that are affected by elevation-induced phase distortions. Errors in the Digital Elevation Model (DEM) can lead to incorrect phase values, so this filter ensures that only scatterers with minimal elevation-induced noise are retained. To mitigate this, a maximum uncorrelated DEM error of 20 m was applied in this study, ensuring that only scatterers with minimal elevation-induced noise were retained.
- **CLAP Filtering:** StaMPS applies a Combined Low-pass and Adaptive Phase (CLAP) filter, which helps reduce spatially correlated phase noise. The effectiveness of this filter depends on grid size and weighting parameters, which control how aggressively noise is removed. For this study, a CLAP window size of 32×32 pixels was used, providing an optimal balance between noise reduction and spatial resolution.

Once StaMPS has determined the most stable scatterers, it applies a probabilistic selection algorithm to finalize the PS points that will be used for displacement analysis. This selection can be controlled using two methods:

- **Fixed Density Threshold:** Ensures that PS points are evenly distributed across the study area, preventing gaps in coverage.

### A.3. PS WEEDING AND PHASE CORRECTION

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- Random Phase Probability Control: Allows StaMPS to dynamically adjust the percentage of selected PS points based on noise characteristics.

In this study, the Density method was chosen for pixel selection, ensuring that scatterers were uniformly distributed across the study area while prioritizing stability. By the end of this step, StaMPS has identified a refined set of highly stable scatterers, forming a strong foundation for further processing. The next phase focuses on weeding out redundant pixels, ensuring that only truly independent and reliable scatterers are used for the final displacement analysis.

## A.3 PS WEEDING AND PHASE CORRECTION

After selecting the initial set of Persistent Scatterers based on temporal coherence, the next critical step in StaMPS processing is PS weeding and phase correction. This process ensures that only the most independent, noise-free, and reliable scatterers are retained for displacement estimation. Even though PS candidates have already been filtered for phase stability, some may still be affected by excessive noise or redundancy, especially if they are located close to each other. To improve the accuracy of displacement measurements, StaMPS applies two key refinements:

- Weeding out redundant or noisy scatterers to improve the precision and spatial distribution of PS points.
- Correcting for spatially uncorrelated look angle errors, which can introduce phase distortions affecting displacement accuracy.

These refinements significantly enhance the reliability of PS-InSAR results, ensuring that only the most stable scatterers are used in the final analysis. One of the first refinements applied in this step is noise-based weeding, which removes scatterers that still exhibit too much phase noise, even after passing the gamma threshold. Some scatterers may be stable in certain interferograms but unstable in others, causing inconsistencies in the displacement time series. To prevent this, StaMPS evaluates the standard deviation of phase noise for each scatterer and removes those that exceed a predefined threshold. For this study, the weed standard deviation threshold was set to 1.0, meaning that scatterers with excessive phase fluctuations were discarded to maintain high-quality displacement estimates. Another important filtering mechanism is proximity-based weeding, which prevents the selection of multiple pixels influenced by the same dominant scatterer. In areas with strong backscattering, such as metallic bridge surfaces, multiple PS points may form

#### A.4. PHASE UNWRAPPING

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too close together, leading to redundant measurements. To avoid this, StaMPS removes nearby scatterers, ensuring that only the most reliable and independent PS points remain. For this study, neighbor-based weeding was enabled, meaning that redundant PS pixels in close proximity were filtered out to prevent duplicate measurements. Lastly, StaMPS applies a maximum noise threshold to eliminate scatterers that show excessive noise across interferograms. However, since PS-InSAR is already designed to select the most stable scatterers, an upper noise limit was not strictly necessary in this case. For this study, the maximum allowed noise was set to infinity, meaning that no additional noise-based filtering was imposed beyond the standard deviation threshold.

Once the PS dataset is refined, StaMPS applies a correction for spatially uncorrelated look angle errors. Since SAR images are captured at an oblique angle, the phase values of PS points can sometimes be affected by small inconsistencies related to satellite viewing geometry. These errors, if left uncorrected, could distort the final displacement measurements. To correct this, StaMPS estimates how the look angle affects phase distortions across different scatterers and applies an adjustment to ensure that relative displacement values remain accurate. This correction is particularly important for monitoring structural deformation, where even small phase inconsistencies can impact the interpretation of long-term displacement trends.

By the end of these steps, the dataset contains only the most stable, independent, and reliable scatterers, ensuring that displacement calculations are not affected by redundant or low-quality pixels. Furthermore, look angle corrections eliminate distortions that could have introduced false displacement signals, improving the overall precision of the dataset.

With this refined PS dataset, the next phase of processing will focus on phase unwrapping, converting phase values into meaningful displacement measurements.

## A.4 PHASE UNWRAPPING

After refining the Persistent Scatterer dataset through weeding and phase correction, the next critical step in StaMPS processing is phase unwrapping. Since radar phase measurements are inherently wrapped, meaning they are confined between 0 and  $2\pi$  radians, phase unwrapping is necessary to reconstruct the true displacement history of the selected PS points. Without this step, large displacements might appear as abrupt jumps in the phase data, making it impossible to accurately interpret deformation trends over time.

StaMPS employs a three-dimensional (3D) phase unwrapping approach, which takes into account both spatial and temporal coherence. Unlike traditional 2D methods, which only process

#### *A.5. TROPOSPHERIC CORRECTION WITH TRAIN*

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one interferogram at a time, the 3D unwrapping technique leverages the full stack of interferograms to provide a more robust and consistent solution. By analyzing phase continuity over time, this approach helps reduce unwrapping errors, particularly in areas where coherence might fluctuate due to environmental or structural conditions. For this study, the 3D unwrapping mode was selected, ensuring that the phase unwrapping process incorporated temporal relationships between acquisitions, resulting in a more reliable displacement estimation.

To further enhance phase unwrapping accuracy, Goldstein filtering was applied before unwrapping. This filter reduces high-frequency noise in the phase measurements, improving the continuity of the unwrapped phase. The filtering strength is controlled by Goldstein Alpha, a parameter that determines the level of smoothing applied. A value of 0.8 was chosen for this study, striking a balance between noise reduction and preserving fine-scale deformation details. Additionally, the Goldstein filter window size was set to 32 pixels, allowing localized phase variations to be smoothed effectively without losing important structural information.

The unwrap grid size, which defines the spatial resolution used for phase unwrapping, was set to 200 pixels. A larger grid size generally helps reduce processing time and improves unwrapping stability, but it can also lead to the loss of finer displacement details. In this case, 200 pixels were selected as an optimal balance, ensuring that the displacement results remained both computationally efficient and spatially accurate.

With these refinements in place, the unwrapped phase values provided a continuous and realistic displacement signal, laying the groundwork for the final interpretation of deformation trends.

## **A.5 TROPOSPHERIC CORRECTION WITH TRAIN**

Once phase unwrapping was completed, a tropospheric correction was applied to remove atmospheric distortions from the displacement measurements. The Earth's atmosphere, particularly the troposphere, can introduce delays in radar signals, which often appear as false displacement signals in PS-InSAR results. These distortions are caused by variations in atmospheric water vapour, which affect the propagation of radar waves. If not corrected, these delays can create misleading deformation trends, making it difficult to distinguish actual structural movement from atmospheric noise.



## A.6. ESTIMATION OF SPATIALLY CORRELATED ERRORS

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To account for this, the TRAIN<sup>1</sup> (Toolbox for Reducing Atmospheric InSAR Noise) module was used. TRAIN applies a linear tropospheric correction model, which assumes that tropospheric phase delays are correlated with elevation. Since higher-altitude areas tend to experience different atmospheric conditions than lower elevations, this correlation can be used to estimate and remove tropospheric phase artifacts from the dataset.

In this study, the tropospheric correction process involved analyzing the relationship between phase delay and elevation, allowing the estimation of atmospheric distortions affecting the interferograms. The correction model generated a tropospheric noise map, which was then subtracted from the unwrapped phase values. This step significantly improved the accuracy of the displacement results by ensuring that the final deformation measurements reflected actual structural movement rather than atmospheric fluctuations.

Figure Placeholder: A sample figure illustrating the linear correlation between tropospheric phase delay and elevation.

By applying TRAIN, the dataset became more robust against atmospheric disturbances, providing a clearer and more reliable interpretation of deformation patterns on the bridge. With these corrections in place, the next step focused on finalizing the displacement and velocity estimations for long-term structural monitoring.

## A.6 ESTIMATION OF SPATIALLY CORRELATED ERRORS

With phase unwrapping completed and tropospheric correction applied, the final refinement step in StaMPS processing involves estimating and correcting spatially correlated errors. These errors, if left unaddressed, can introduce systematic distortions in the displacement measurements, making it difficult to differentiate actual structural movements from residual noise. Even though previous processing steps, such as phase unwrapping and tropospheric correction, help reduce phase inconsistencies, there are still lingering spatially correlated distortions due to errors in the DEM, atmospheric artifacts, and orbital inaccuracies.

One of the primary sources of these errors is the spatially correlated look angle (SCLA) error, which arises due to inaccuracies in mapping the DEM into radar coordinates. Since PS-InSAR displacement measurements rely on the assumed elevation of each PS point, any discrepancies between the actual terrain elevation and the DEM data can introduce broad-scale phase distortions.

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<sup>1</sup><https://github.com/dbekaert/TRAIN>

#### *A.6. ESTIMATION OF SPATIALLY CORRELATED ERRORS*

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Additionally, residual atmospheric phase delays (those that were not fully corrected by TRAIN) can still persist and affect the final displacement results.

To correct these effects, StaMPS applies a low-pass spatial filter, which helps separate broad-scale errors from localized deformation trends. The basic assumption here is that real deformation patterns should exhibit localized consistency, whereas spatially correlated noise tends to affect larger areas uniformly. By filtering out these long-wavelength noise patterns, the dataset is refined, ensuring that the displacement signals more accurately reflect actual structural movement. Once these refinements were complete, the dataset was now fully processed and prepared for final interpretation.

# APPENDIX B

## SHAP-DISPLACEMENT FOR SENTINEL-1 PS POINTS

This appendix presents the complete SHAP contribution analyses and displacement time-series results associated with the PS-InSAR anomaly detection framework discussed in Chapter 4.

